Toward Platform-based Building Design

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by

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Abstract

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The building industry is responsible for over 40% of the world's energy consumption, making it imperative to develop more efficient building designs to reduce energy usage and minimize environmental impact. However, the current building design process is highly fragmented, resulting in inefficient and sub-optimal designs. Although the digitalization of the building industry happened nearly at the same time as the electronics industry, the latter has become fully automated, whereas the building industry still lags behind.

This dissertation identifies the challenges in the building design process that hinder automation and proposes a platform-based approach as part of the solution. Platform-based design enables the development of common interfaces for greater consistency and efficiency in the design process, along with modularity that breaks down complex systems into smaller, more manageable modules. This facilitates easier design iteration and adaptation to changing requirements, while also allowing for the reuse of design components across different projects, saving time and resources.

In addition, the dissertation explores the potential of levels of abstraction in building energy models to better support the design process without requiring a full building model at early design stages. This can help reduce design iterations and save time and costs. Finally, we streamline the process of constructing building models as a step towards automated design. Although fully automated design is yet to be realized, this streamlined process serves as a potential starting point for achieving automation in the future.

To my family

Contents

Acronyms

AHU Air Handling Unit. 63, 64, 70

AI Artificial Intelligence. 15, 29

AIA American Institute of Architects. 23, 39

ANN Artificial Neural Network. 58

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers. 11, 14, 32, 46

BEM Building Energy Modeling. 37, 39, 42, 43

BIM Building Information Modeling. ix, 7, 10, 12, 15, 17, 23, 28, 32, 33, 35, 36, 38, 39, 83

BOPTEST Building Optimization Testing Framework. 75

BPS Building Performance Simulation. 36, 37, 39, 40, 55

BREEAM Building Research Establishment Environmental Assessment Method. 3

CAD Computer-Aided Design. 7, 17, 20, 24, 25, 39

CAD/E Computer-Aided Design and Engineering. 13, 30

COBie Construction Operation Building Information Exchange. 38

COP Coefficient of Performance. 46, 50

DEF Data Exchange Format. 21, 25

DOE Department of Energy. 43

DRL Deep Reinforcement Learning. 58

DT Digital Twin. 54–56, 76, 78

EDA Electronic Design Automation. 8, 11, 18, 20–22, 29, 80

FMI Functional Mock-up Interface. 75

FPGA Field Programmable Gate Array. 21

GA Genetic Algorithm. 11, 13, 14, 30–32

GAN Generative Adversarial Network. 11, 13, 30

gbXML Green Building XML. 7, 25, 37–39

GD Generative Design. 12, 13, 30

GHG Greenhouse Gas. 1, 18, 35

HDL Hardware Description Language. 19, 21

HLS High-Level Synthesis. 21

HVAC Heating, Ventilation, and Air-Conditioning. 1, 6–8, 14, 18, 23, 28, 29, 32, 36, 45, 46, 50, 58, 60, 64, 75, 80, 81

IC Integrated Circuit. 18–20

IEA International Energy Agency. 4

IFC Industry Foundation Classes. 7, 25, 28, 37–39

IoT Internet of Things. 5, 6, 15, 56, 58

IP Intellectual Property. 20

IT Information Technology. 15

LBNL Lawrence Berkeley National Lab. 75

LEED Leadership in Energy and Environmental Design. 3, 10

LEF Library Exchange Format. 21, 25

LoD Level of Detail. ix, 23, 39

MEP Mechanical, Electrical, and Plumbing. 5, 12, 14, 28, 40

MPC Model Predictive Control. 58

MSE Mean Squared Error. 68, 70, 72, 73

MVD Model View Definition. 25

NLP Natural Language Processing. 12

NZEB Net-Zero Energy Building. 4, 54

OAE Outdoor Air Emulator. 63

PBD Platform-based Design. vii, viii, 29, 32–34, 75, 76

PCM Phase Change Material. 3, 5

PID Proportional-Integral-Derivative. 58, 72

RC Resistor-Capacitor. 59, 72

RF Random Forest. 70

SA Simulated Annealing. 13, 30

SHGC Solar Heat Gain Coefficient. 45–47, 50

SoC System on a Chip. 20, 21

SPICE Simulation Program with Integrated Circuit Emphasis. 20

SVM Support Vector Machine. 58

UAV/UGV Unmanned Aerial/Ground Vehicles. 15, 31

VAV Variable Air Volume. 64, 70

VHDL Very High Speed Integrated Circuit-Hardware Description Language. 21

WWR Window-to-Wall Ratio. 45, 46, 50

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Chapter 1

Introduction

1.1 Motivation

Climate change is a global crisis that significantly impacts the environment, human health, and the economy. It is causing more frequent and severe weather events, such as floods, droughts, and wildfires, which can have devastating consequences for communities and infrastructure [72]. These events are also leading to food and water shortages, displacement of people, and loss of biodiversity [155]. Carbon emissions are a major contributor to climate change, and their levels are increasing every year [80]. Burning fossil fuels for energy, transportation, and industrial processes releases carbon dioxide and other Greenhouse Gas (GHG) into the atmosphere. These gases trap heat and lead to global warming, causing severe impacts on the planet. As a result, there is a need to reduce energy consumption and carbon emission worldwide. These can be achieved by reducing GHG emissions, improving energy efficiency, transitioning to cleaner and more sustainable energy sources, and restoring forests.

Buildings and the construction industry are pivotal in energy consumption and carbon emissions in the United States. They account for approximately 40 % of energy consumption and carbon emissions in the country [4] as shown in Figure 1.1. A major contributor to building energy consumption is Heating, Ventilation, and Air-Conditioning (HVAC) systems, which are responsible for over 50% of energy usage in buildings [2, 3] as shown in Figure 1.2. Other factors that contribute to energy consumption in buildings include lighting, refrigeration, appliances, and electronics. Buildings are not only responsible for the energy used in the operation stage but also during their construction, renovation, and demolition phases. Therefore, reducing energy consumption and carbon emissions in the building sector is essential to combat climate change.

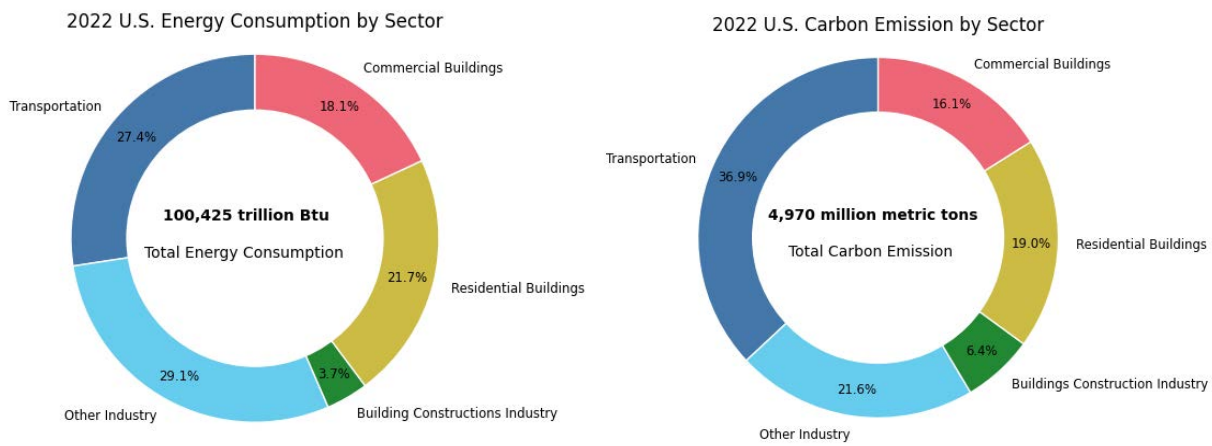

Figure 1.1: 2022 U.S. Energy consumption (left) and carbon emission (right) by sector [4]. The building construction industry sector is estimated based on [106].

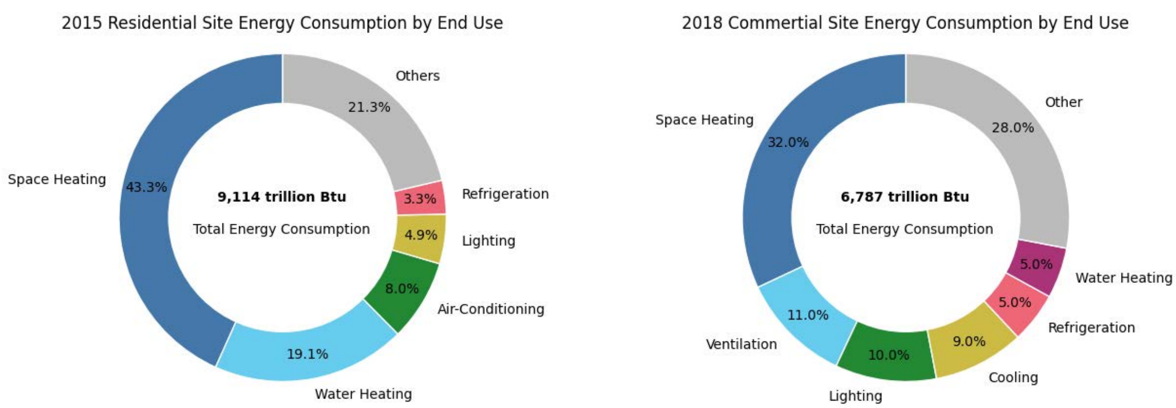

Figure 1.2: 2015 U.S. residential site energy consumption by end-use (left) [2] and 2022 commercial site energy consumption by end-use [3].

1.2 Background

To reduce the carbon footprint and energy consumption of the building sector, research has focused on various areas, including building design, renewable energy, energy storage, smart building technologies, occupants' behavior, and building retrofitting.

Building Design

Research on building design can help in developing energy-efficient buildings that require less energy to heat, cool, and operate. This can be achieved through the use of passive design strategies such as shading, insulation, and natural ventilation. The orientation, shape, and shading of a building impact the amount of radiation that its surface is exposed to, potentially leading to an increase in cooling needs [189]. The building envelope, such as roofs, walls, and doors, is another factor that plays an important role in regulating the internal temperature [138]. For example, a well-insulated roof can help to reduce heat loss during the winter months, while walls with high thermal mass can help to absorb and store heat during the day and gradually release it at night, helping to maintain a comfortable internal temperature. Additionally, properly sealed doors and windows can prevent drafts and heat loss, improving the overall energy efficiency of the building. In recent decades, researchers have also explored the application of Phase Change Materials (PCMs) in building envelopes as a promising approach for thermal energy storage in buildings [195]. As a result, optimizing building envelope parameters can minimize heating load and improve energy efficiency. Other passive techniques include ventilation, nocturnal convective cooling, radiant cooling, direct and indirect evaporative cooling [90]. These methods offer sustainable and energy-efficient ways to cool buildings without relying heavily on mechanical cooling systems.

Sustainable building materials can further reduce carbon emissions, making them a crucial aspect of modern building design. GHG labeling [204] is increasingly important as it provides stakeholders with information on the amount of carbon emitted during material production and transportation, allowing designers to make informed decisions about the environmental impact of materials used at the early stages of design. By selecting appropriate materials, designers can considerably reduce the environmental impact of a building. In addition, green building certification programs, such as Leadership in Energy and Environmental Design (LEED) and Building Research Establishment Environmental Assessment Method (BREEAM), encourage the adoption of sustainable practices and help building owners and operators makes informed decisions to reduce energy consumption and carbon emissions.

The above-mentioned design strategies emphasize how the early stages of building design affect its energy performance and carbon emission. The MacLeamy Curve [136], as shown in Fig 1.3, describes that the ability to impact the cost and function of a building design is the highest during the early stages of design. During these stages, design decisions can greatly impact the energy efficiency and the overall performance of the building, while changes can be made relatively easily and at a lower cost. As the design progresses to the later stages, the ability to make substantial changes decreases while the cost to make changes increases. Therefore, it is crucial to consider environmental impacts and energy efficiency throughout the entire design process, with a focus on the early stages to maximize the benefits of design decisions on building performance.

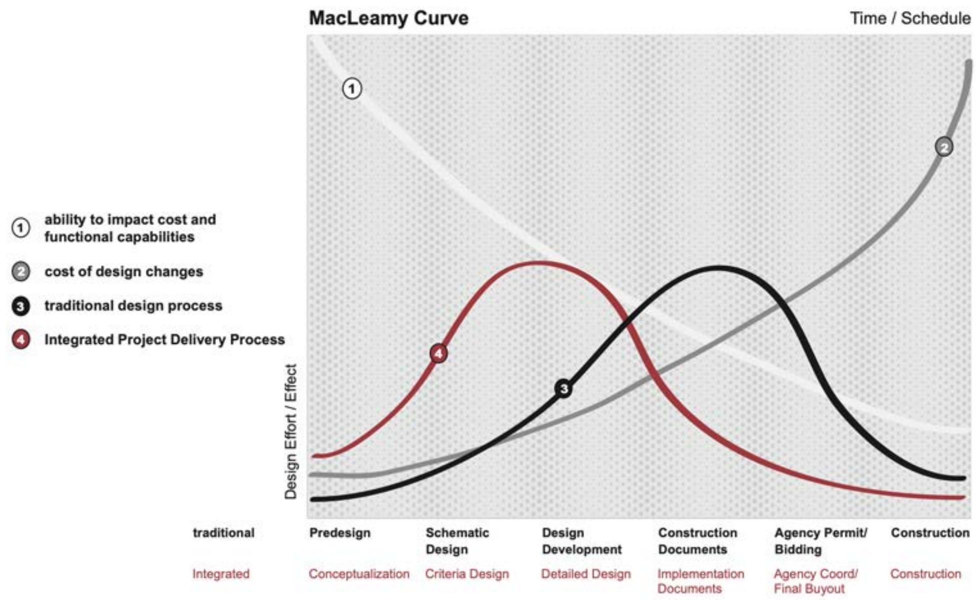

Figure 1.3: The MacLeamy Curve [60].

Renewable Energy

Renewable energy is increasingly recognized as an essential resource for reducing reliance on fossil fuels and mitigating carbon emissions in the building sector. Among the strategies employed to achieve carbon reduction, Net-Zero Energy Building (NZEB) is gaining ample attention. NZEB is a building that produces the same amount of energy it consumes over a period of time [158]. NZEBs utilize renewable energy sources, such as solar panels, wind turbines, and geothermal systems to generate electricity and heat. The energy produced by these sources is typically used to power the building's lighting, heating, and cooling systems, appliances, and other electrical equipment. By reducing or even eliminating the building's dependence on fossil fuels, NZEBs offer a promising opportunity to reduce GHG emissions and address climate change. Governments worldwide have also introduced new policies and regulations aimed at promoting NZEBs. For example, California has set a target to make all new commercial construction NZEBs by 2030 [54]. International Energy Agency (IEA) has also published a report detailing the roadmap to reach net zero by 2050, limiting the rise in global temperature to $1.5°C$ [6]. With continued efforts and commitments from governments and industries, NZEBs can play a vital role in achieving a sustainable future.

Energy Storage

The integration of renewable energy sources into the electric grid has created a need for energy storage systems that can store excess energy when it is available and release it when it is needed. Renewable energy sources are often intermittent because their availability fluctuates depending on the weather conditions. As a result, energy storage systems have become a critical component of the energy infrastructure, enabling the effective use of renewable energy sources and reducing the reliance on grid electricity [97]. Energy storage systems come in various types, including batteries and thermal storage. Batteries are commonly used in smaller-scale energy storage applications, such as residential and commercial buildings [142]. They are efficient, reliable, and can be easily installed. Thermal storage, on the other hand, stores thermal energy in materials. For example, thermal storage can be implemented in building envelopes, ventilation systems, and solar-thermal systems via PCMs [143]. PCMs store large amounts of thermal energy by changing their state, such as from a solid to a liquid, or vice versa. When the temperature of a PCM rises above a certain threshold, it changes state and stores the excess thermal energy. Later, when the temperature falls below the threshold, the PCM releases the stored thermal energy. This process can be repeated over and over again, making PCMs an effective energy storage solution. Energy storage systems are crucial to the integration of renewable energy sources into the electric grid.

Smart Building Technologies

The Internet of Things (IoT) has brought about opportunities for integrating real-time sensor data with BIM, enabling real-time monitoring of buildings [179]. IoT devices can collect real-time data on various aspects of buildings, such as temperature, humidity, occupancy, and lighting. For example, IoT devices can sense occupancy and human activity, resulting in improved energy consumption estimation, intrusion detection in residential homes, and regulation of lighting and temperature based on occupancy [208, 157]. Furthermore, data-driven algorithms can analyze the collected data to identify patterns and trends, providing valuable insights into the performance of building systems. For instance, machine learning algorithms are used for predictive maintenance in the Mechanical, Electrical, and Plumbing (MEP) systems of a building [49]. These algorithms identify and address potential issues before they become critical, reducing energy waste caused by inefficient equipment operation. Additionally, the collected data can be used to train control algorithms that optimize building operation, such as HVAC [109] and lighting systems [206] to optimize energy consumption and occupant comfort. These algorithms continuously adapt the control strategies based on real-time data, resulting in more efficient operation. IoT also enables participation in demand response programs, where buildings can respond to utility signals to reduce or shift energy usage during peak demand periods [94]. This helps in reducing strain on the electric grid and avoiding the need for additional power generation, which can contribute to lower carbon emissions. Smart building technologies empower building operators to make informed decisions based on data, optimize energy usage, identify and address inefficiencies, and minimize energy waste. This ultimately results in improved energy efficiency and reduced carbon emissions.

Occupants' Behavior Change

IoT devices can also be utilized to actively engage and educate building occupants about their energy usage patterns and behaviors, offering feedback and recommendations for adopting more sustainable energy practices. Furthermore, they can be integrated with gamification techniques to incentivize and motivate occupants to adopt more sustainable energy practices. Konstantakopoulos et. al. [118] introduced a social game framework that encourages occupants to actively participate in energy-saving activities and compete with each other to achieve energy-saving goals. Moreover, IoT devices can provide educational resources to occupants, such as tips, tutorials, and information on energy-saving practices [42]. Occupants can access this information through user-friendly interfaces on their devices, providing them with the knowledge and tools to make informed decisions about their energy usage. In 2022, California experienced a severe heat wave, which resulted in an emergency alert being sent to millions of phones, urging occupants to conserve energy [176]. During extreme weather conditions, the demands for electricity to power air conditioning systems and other cooling devices surge, putting a strain on the power grid. To avoid power outages and blackouts, emergency alerts are issued to the public, requesting them to reduce their energy consumption and conserve energy. This situation underscores the significance of human active participation in energy conservation efforts.

Building Retrofitting

Retrofitting is a process that upgrades or modifies existing buildings with energy-efficient technologies, systems, and practices to enhance their performance and reduce their environmental impact. As energy efficiency requirements evolve over time, older buildings constructed under less stringent regulations tend to have lower energy efficiency compared to newly constructed buildings. This is due to advancements in building codes and standards, as well as the availability of more energy-efficient technologies. Therefore, retrofits play a vital role in improving energy efficiency by bringing older buildings up to modern energy efficiency standards [7]. It is particularly important when it comes to space heating and cooling, as these systems account for a large portion of a building's energy consumption, as depicted in Figure 1.2. Therefore, retrofitting HVAC systems with energy-efficient technologies can greatly improve a building's energy efficiency and reduce its carbon emissions [44]. Furthermore, retrofitting can also encompass the installation of renewable energy systems, improvements in lighting systems, and enhancements to the building envelope to optimize energy use and reduce environmental impact [15]. By upgrading and modifying older buildings with energy-efficient technologies, retrofits can contribute to energy savings and environmental sustainability.

1.3 Research Gaps

The process of building design involves multiple parties, but it is often not streamlined, resulting in redundant efforts from various research groups. Despite the availability of numerous energy-efficient technologies and practices, the lack of interoperability and integration among them poses challenges in implementing a unified approach to achieve optimal building performance. The foremost problem that requires resolution is a standardized platform that can seamlessly integrate different technologies and practices. For example, building geometry, HVAC systems, performance simulation programs, and renewable energy systems may operate in silos without a common platform for data exchange, communication, and coordination. Although data standards such as Industry Foundation Classes (IFC) [107] and Green Building XML (gbXML) [86] exist for data exchange, they do not fully represent all aspects of building systems. Autodesk Revit, a Building Information Modeling (BIM) software, has emerged as a promising common platform for integrating various systems, allowing other software to function as plug-ins within Revit. Despite its potential, there are still limitations that hinder its full realization, primarily revolving around interoperability between Revit and other software applications. This can result in sub-optimal performance, and due to the lack of integration, the potential for energy savings may be limited. This dissertation seeks to identify and address some challenges that hinder the transformation of fragmented building design into an integrated platform-based design.

1.4 Research Questions

The dissertation looks to answer the following research questions.

1. What are the key challenges and obstacles that prevent building design from being fully automated, and how can these be addressed?

The electronic design industry has undergone a remarkable transformation from traditional hand-drawn designs to modern automated design processes. In the 1960s, the first Computer-Aided Design (CAD) tools emerged [178], revolutionizing the way designs were created by introducing graphical interfaces and enabling more efficient and precise drafting. Over time, technologies have evolved to encompass simulation, verification, and high-level synthesis, allowing for faster and more accurate design iterations.

In contrast, the Building Information Modeling (BIM) concept, which emerged in the 1970s, aimed to bring similar advancements to the fields of building design [68]. BIM is a digital representation of a building's physical and functional characteristics, including its geometry, spatial relationships, materials, and performance data. It is intended to enable collaboration, coordination, and data-driven decision-making throughout the entire building lifecycle, from design and construction to operation and maintenance. However, despite the potential benefits of BIM, the building design process has not yet been fully automated. While BIM tools have become widely adopted in the construction industry, the process of creating and managing building models still requires notable manual effort. Architects, engineers, and other stakeholders often need to input data, interpret and analyze information, and make subjective decisions based on their expertise and experience. The complexity of building design, with its diverse requirements, regulations, and stakeholder interactions, presents challenges for achieving full automation.

Chapter 2 of this dissertation will delve into this research question by drawing a comparison between the Electronic Design Automation (EDA) industry and the building design industry. Through this comparison, gaps in the building design industry will be identified, and frameworks and examples based on a modular and platform-based approach will be proposed as a potential solution.

2. What is the appropriate level of abstraction for building energy models to effectively assist in the design process?

One of the reasons why electronic design has been able to achieve across the board automation compared to building design is the clear definition of the level of abstraction in the various design stages from system to layout design. Its process involves well-defined design protocols, with clear hierarchies and abstraction layers. On the other hand, a building design process does not have a standardized design protocol and often varies from firm to firm and location to location. Building projects are unique and involve diverse stakeholders with different design preferences, construction practices, and regulatory requirements. The non-uniformity and variability in design practices create difficulties in achieving full automation in building design. In order to progress towards automation in building design, it is crucial to have simulation tools that can support various stages of the design process. Although energy simulation tools for buildings do exist, they often rely on detailed parameters such as building geometry, building envelope, and HVAC systems, which may not be consistently available during the early design stages. As a consequence, accurately estimating the energy performance of a design at an early stage becomes tedious and challenging. In Chapter 3, we propose a modeling approach that utilizes sensitivity analysis and probability to facilitate informed decision-making, with the objective of optimizing energy consumption throughout the entire design process.

3. How to streamline the process of constructing building models from existing data structures?

Computer models that capture the various aspects of building performance play a crucial role in the design and operation of buildings, allowing for the simulation of various what-if scenarios to assess their performance. These models can be categorized as *white box*, *gray box*, or *black box* models, each with its level of detail and complexity. However, the process of model construction often requires significant manual efforts, from data mapping to parameter calibration. This can be time-consuming and labor-intensive, requiring expert knowledge and expertise. Moreover, building models are not always consistently maintained from the design phase to the operation phase, resulting in discrepancies and inconsistencies in their performance predictions. There are also no clear criteria to determine the most suitable model for a specific application.

In Chapter 4, our aim is to streamline the building model construction process by leveraging available data structures and a platform-based design framework, reducing manual efforts and minimizing errors. Furthermore, we develop a performance metric example that can assist in determining the most suitable model for a given approach. The metric considers factors such as accuracy, execution time, measurement granularity, prediction horizon, and output resolution. This will help designers and researchers in selecting the most appropriate building model for their specific needs, ensuring that the right model is used for the right purpose, and enhancing the overall effectiveness of building models.

Chapter 2

From Electronic Design Automation to Building Design Automation [1]

2.1 Background

Design automation refers to the utilization of software tools to aid designers in creating and delivering products more efficiently by eliminating the need for manual labor that was required with traditional design methods. It has gained prominence in several industries, including electronics [137], automotive [125], aerospace [166], and manufacturing [134], where it has enabled significant advancements in product development and manufacturing efficiency. However, in the building industry, design automation has not been adequately utilized and has yet to become a standard part of the design process.

The building design process involves several parties, including architects, engineers, building authorities, clients, financial institutions, and constructors. Traditionally, different development disciplines are siloed from each other and each section is assembled after the product is set in stone. However, this separate independent design results in not only personnel dependencies that increase the time of the critical path from initial design to complete development but also in objective inefficiencies that result from a lack of communication during the development process. Stronger communication between all the stakeholders would be essential to improve the development process for energy-efficient buildings.

Reed et al. [153] developed an integrative building design framework to guide involved parties to communicate more efficiently. Leadership in Energy and Environmental Design (LEED), a green building rating system, also promotes an integrative process by providing one point in credit to encourage synergies between different disciplines during the design process. Though Building Information Modeling (BIM) and the integrative framework exist for more than a decade, the current building industry still has yet to adapt to the integrative design process. Challenges include integration between different software and tools,

[1] This chapter is a modified and extended version of manuscripts that are preparing for submission with the preprints available in reference [130, 132].

building complexity, communication barriers between different design teams, and limited standardization for building design practices.

The building design process shares several similarities with the electronic design process. They both require an initial concept or idea to be developed and refined through multiple stages of design and prototyping. In both cases, the design must consider various technical requirements, such as functionality, safety, and durability. Additionally, both building and electronic design require collaboration among different professionals, including engineers and designers. Furthermore, both design processes often involve the use of specialized software and tools to aid in the creation and testing of the design. However, while the electronic industry has evolved from hand-drawn design to Electronic Design Automation (EDA), the building industry has yet to fully utilize design automation technologies.

Although there has been research on design automation techniques in subsystems of building design, such as structural form [209], floor plan [12, 202, 77], façade [193, 184, 145], and HVAC [24, 215], these techniques are rarely applied in the current building industry. One of the main reasons is the absence of standardized input-output relationships for each component. This lack of standardization makes it challenging to reuse components across different designs. Consequently, it becomes difficult to remove and replace a specific component or technique in another design, as there is no assurance that the inputs and outputs will align correctly. Additionally, each building type has its unique requirements, constraints, and regulations, resulting in a tailored design process for each specific type and location. However, by leveraging automation, designers can complete tasks more efficiently and accurately, reduce errors and inconsistencies, reduce or eliminate manual labor, ensure that design standards and procedures are consistently followed, enable easy modification and adjustment of designs, and experiment with new and innovative design ideas.

In this chapter, we explore existing design automation efforts in the building industry, use EDA as a reference to identify the areas where building design falls short in realizing automation, and propose modular and platform-based approaches to bridge the gaps and accelerate the adoption of automation in building design processes.

2.2 Related Work

Traditional design approaches are often limited by the experiences and knowledge of human designers. Key design decisions are often already made before assessment due to budget, time constraints, and project requirements. In addition, design evaluations primarily serve to meet building codes such as energy standards, ASHRAE 90.1 [95], and thermal environmental conditions, ASHRAE 55 [17]. Building design has the potential to be further optimized in order to create a more energy-efficient and environmentally-friendly solution. Advances in computing technologies and machine learning algorithms have enabled the possibility of exploring a larger design space that may be overlooked by designers. For example, Generative Adversarial Network (GAN) can be used to generate new building designs [177, 203], Genetic Algorithms (GAs) can be used to optimize building parameters and configurations with an objective of energy efficiency and thermal comfort [187, 126], and Natural Language Processing (NLP) algorithms can analyze building codes and regulations [214, 62]. Existing BIM software, such as Autodesk Revit 2021 [88], has the capacity to implement Generative Design (GD) for building geometry. It allows users to input design goals and constraints, and employs GD techniques to generate multiple design options to meet those objectives. It can be used to optimize building designs for structural performance, energy efficiency, and sustainability. However, limitations exist in the user interface, data availability, complex structures, and processing speed.

By utilizing advanced computational tools, designers can generate a set of high-quality solutions that meet design objectives and constraints, such as energy efficiency, functional performance, and cost-effectiveness. The process can help accelerate the design processes, reduce costs, and improve the overall quality of building design. The following section reviewed prior studies of design optimization and automation in different disciplines of building design including building structure and layout, Mechanical, Electrical, and Plumbing (MEP) systems, and construction.

Building Structure and Layout

The building design process starts with an understanding of the project goals, scope, and budget. Then the design team conducts a preliminary analysis of the building site and explores different design options. Once the architect proposes a design concept for the building, which is then reviewed by the structural engineer to ensure that it meets requirements for structural feasibility and compliance with relevant building codes. The communication between architects and engineers involves back-and-forth communications to arrive at a final design decision that meets both the aesthetic and functional requirements of the building. There is little to no real-time feedback when architects design the building. The back-and-forth communications between architects and engineers can be reduced through dynamic feedback on design tools. With real-time feedback, architects can quickly evaluate the impact of their design choices on structural soundness, carbon footprint, energy efficiency, and cost-effectiveness. Furthermore, if designers can get recommendations on potential design solutions with a better energy or carbon perspective, it not only saves design effort by improving the design pipeline but also creates a more sustainable design. While the role of structural engineer can't be fully replaced, machine learning can assist in performing structural analysis, optimizing building parameters and functional performance, and estimating cost.

Building structural design consists of form, floor plan, façde, and structural components such as acoustic design and fire-resistant integration. The structural systems are responsible for energy and carbon emissions through the production and assembly of structural materials [9]. As a result, it is crucial to take carbon emissions into account during construction design and material selections. Hammond et al. [96] created a database of 200 construction materials with their carbon and energy emission values. The database can facilitate estimating the carbon intensity of a building structure at the early stage of building design. However, existing databases are sparse and are often constrained by building types, locations, and production companies. To address the issue, Weber et al. [197] use a GD approach to perform carbon analysis of steel framing systems based on building massing with 17% error margin compared to actual buildings. Rather than providing an early-stage carbon assessment of a building, other research used optimization techniques to identify optimal building structural form.

The term "building structural form" refers to the overall shape, configuration, and style of a building. It involves the design of the physical appearance of a building. Computer-Aided Design and Engineering (CAD/E) software has the capability to automatically generate different options for building forms based on design constraints [210]. Additionally, GA is also used to explore a wide range of design options and find optimal building forms based on energy performance [209, 39, 188]. Zhang and Blasetti applied GAN to study a style transfer of two buildings to inspire architects in various building forms [211].

Once the structural form is established, the floor plan is developed. Designers sought automation during layout design for the purpose of faster design, design exploration, visual comforts, material effectiveness, and optimization [196]. The algorithms take building area or boundary as an input and output the program layout. The existing optimization methods include physically based [12], evolution algorithm [202], and Simulated Annealing (SA) [77]. However, challenges still exist in encoding social equity into a machine learn-able language. As a result, floor plan generation methods at the current stage can't replace experienced human designers completely, but rather, serve as a guide to the designer.

Façade design is another important element in the architectural design of a building. A façade is the exterior wall or face of a building. It is pivotal not only in the aesthetic aspect of a building but also in energy efficiency, weather resistance, thermal and acoustic insulation, and lighting regulation. Wang et al. [193] used a parametric optimization method to discover optimal façade design of naturally ventilated residential buildings for better thermal comfort and energy savings. Torres and Sakamoto [184] determined optimal façade design for daylight performance in a building using GA. Weber et al. [198] explored exoskeleton façade design with parametric models based on different shading strategies for passive solar gain control and embodied carbon of materials. GAN is also used in generating a visualization of facçade with existing facçade design image as training inputs [145]. Though the mentioned studies showed promising results in achieving a better design of façade, most research didn't consider all objectives when forming an optimization problem. If all factors, such as aesthetic, energy, thermal, acoustic, and daylight, are considered, the formulated problem may become infeasible. The trade-offs between different objectives are crucial in the design decision.

Structural components are physical elements that make up the building's structure, such as beams, columns, walls, slabs, and foundations. At this stage, the process entails the selection of structural components that meet design constraints. Adeli and Park [1] applied a neural dynamics technique to design space trusses with the objective of minimizing the materials' weight. Bennage and Dhingra [27] used SA to optimize cross-sectional areas of trusses. Garrett and Fenves [85] proposed a knowledge-based method to generate the detailed design of structural components. Caldas and Norford [40] studied GAs on optimal or near-optimal selections of construction materials. Due to the availability of various construction materials, there could be several ideal solutions that meet the requirements for environmental performance. Nevertheless, the final design decision still requires the expertise of designers. Although the approach can offer useful information to designers, certain limitations exist, such as high computational expenses for a bigger design area, infeasible solutions, and the absence of a comprehensive global construction materials database.

MEP Systems

Mechanical, Electrical, and Plumbing (MEP) systems are the next integral part of building design. The mechanical systems include HVAC systems that regulate temperature, humidity, and air quality in the building. The electrical systems include lighting, power distribution, and fire alarm systems. The plumbing systems include water supply, drainage, and waste management systems.

Optimizing the design of HVAC systems is crucial for achieving energy efficiency in buildings, as these systems are responsible for using over 50% of the electrical energy in buildings [52]. One challenge in the current design of HVAC systems is that the system is often oversized due to design safety factors and a lack of accurate building load calculations [63]. Oversizing the HVAC units has a major impact on energy inefficiency, cost, and thermal comfort. Trace 700 [186] is currently the most widely used HVAC sizing tool in the industry. Once the system is sized, little to no automation exists in the industry during the HVAC design process. Research studies have attempted to automate the design process of HVAC systems in component selection, topology, and duct design. Zhang et. al. developed an automatic HVAC configuration of a two-zone model using GA [215]. The problem is formulated by optimizing three sub-systems: the decision of system type, the selection of components, and the choice of control strategies. However, one of the existing recommended HVAC configurations developed by ASHRAE [154] still outperforms the resulting synthesis through optimization. Another limitation is that the optimization problem may become infeasible for a larger system than the provided example. Asiedu et al. also use GA to optimize HVAC air duct system design with the objective of minimizing the life-cycle cost [18]. While achieving complete automation in HVAC design is not feasible at present due to the lack of standardization in HVAC design practices across different regions and non-uniformity in HVAC components and pricing, machines can assist in performing repetitive tasks such as duct routing and offering suggestions to designers. Furthermore, the rule-based approach used in HVAC design guidelines presents a potential avenue for future design automation in the field. The coordination between the three systems (mechanical, electrical, and plumbing) also poses a challenge during the MEP system design. Lu et al. [133] proposed a rule-based engine via Revit to facilitate the routing of the three systems. Designing and integrating MEP systems into a building is critical to ensure safety, thermal comfort, and functionality for its occupants. Furthermore, proper design and installation of MEP systems can also result in energy savings, lower operating costs, and carbon reduction.

Building Construction

BIM systems are often not fully utilized in the construction industry, even though the construction process is recorded in BIM, tremendous amounts of time and money can be saved. One reason that this hasn't been done is that BIM requires specific hardware specs for full functionalities and the equipment is often challenging at the construction site. Although the industry is working toward creating more agile apps for on site applications in construction, the functionalities for data exchange and management are still limited. Another reason is that manually inputting construction progress is tedious and time-consuming. However, with the advance in Artificial Intelligence (AI) and Internet of Things (IoT) systems, automatic data collection on-site during construction becomes possible. Technologies that have been applied to the automated data acquisition on the construction site include enhanced IT, geo-spatial positioning systems, 3D imaging, and augmented reality [147]. Asadi et al. [16] proposed utilizing Unmanned Aerial/Ground Vehicles (UAV/UGV) to map the construction environment for accessing the current progress. Zhang et al. [212] explored automation between BIM and robotics in the construction process. They proposed a framework for re-standardizing information flow during the construction process to enable automation for planning and executions. Cheng et al. [50] used real-time positioning sensors to monitor dynamic resources such as personnel, equipment, and materials for safety during field operations.

Other than using AI or IoT technologies, in recent decades, the concept of modular buildings has been prevalent in the construction industry due to its higher efficiency and productivity. Modular building is a concept that fabricates modules off-site as units and assembles the units on-site [87]. The benefits include reducing construction time, producing less waste, causing less disruption in the surroundings, reducing labor requirements, and providing more flexibility for dynamic building layout adjustments during the progress [31]. Research has shown that with a modular design of a building, the construction process can become greatly streamlined in planning, off-site prefabrication, transportation, and on-site assembly with minimal human interventions [22]. There are still limitations and obstacles for the current construction industry to become fully automated. Transitioning from a well-developed traditional construction practice to an AI-based modular approach requires additional risk, cost, and safety assessments. In addition, design guidelines for building modules need to be standardized for enabling wide applications of the pre-fabricated modular structures. Standardized guidelines allow architects and engineers to expand modular libraries to further create flexibility in the design process. Lastly, coordination and management of robots on construction sites are still a challenging task [89]. Though full automation in construction is still at an early stage in development, existing technologies show promising results in realizing automated construction.

2.3 Building Design Process

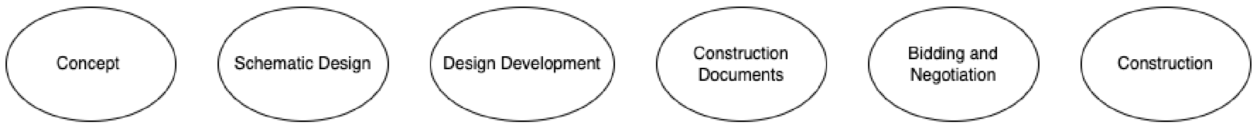

Figure 2.1: Building Design Workflow

Building design has a significant impact on energy consumption and the worldwide carbon footprint. The following sections discuss the state-of-the-art building design workflow, common software tools used in building design, and the negative consequences of poor building design.

Design Workflow

The building design workflow is a complex and iterative process that involves various stages and stakeholders. It is generally split into six different stages: concept, schematic design, design development, construction documents, bidding and negotiation, and construction as shown in Figure 2.1. The absence of an arrow connecting to each node suggests that the building design process is not a linear left-to-right process but rather an iterative one. This means that the design goes through several stages and can backtrack to previous stages for refinement at any point in the process. For example, during the construction of a building that may take several years, the building codes or regulations may change, necessitating design changes in the early design stages. Therefore, the design process requires a flexible approach to accommodate changes in requirements and constraints, ensuring that the final design meets the necessary standards and regulations.

The concept design stage involves gathering information about the project's goals, site, budget, and other constraints. It may also include conducting site analysis and surveys and reviewing zoning regulations. The schematic design involves developing preliminary design concepts, sketches, and drawings that capture the client's requirements and vision. Generally, the building's form, size, and general layout are defined at this stage. In the design development stage, the preliminary design is further developed, refined, and detailed. It includes more detailed drawings, specifications, and material selections. During the construction documents stage, all the design documents are prepared into detailed construction documents that include detailed drawings, specifications, and instructions for the contractors to follow. After completing the construction documents, the next step entails soliciting bids from contractors and engaging in contract negotiations. Lastly, the construction stage involves overseeing the construction process to ensure that the project is built according to its design and specifications.

Throughout the process, the building designers will work with various stakeholders, including the client, engineers, contractors, and government officials, to ensure that the project meets the client's requirements, complies with regulations and standards, and is constructed safely and efficiently. The process is often iterative, with the designer revising the design as new information and feedback are received.

Building Design Software Tools

The building design process relies heavily on software tools to aid in the creation, management, and execution of design projects. Some of the most common software tools used in building design include Computer-Aided Design (CAD) software, BIM software, energy modeling software, project management software, and other analysis software. CAD software is used to create detailed 2D and 3D designs of building components. BIM software is a collaborative tool that allows architects, engineers, and contractors to work together in an integrated platform. This software provides a shared space for design and construction data, enabling all parties to view, edit, and comment on the project in real-time. The most common ones are Autodesk Revit [20], ArchiCAD [92], and Bently OpenBuildings Designer [28]. There are various data structures used to store information in BIM software. Luo et al. [135] have summarized 24 different data tools for representing and managing building data. These data tools help to organize and structure information in the BIM, enabling more efficient and accurate design, construction, and maintenance processes. Energy modeling software plays a crucial role in simulating building energy use and identifying opportunities for energy optimization and savings. By using these tools, designers can make informed decisions about building materials, heating and cooling systems, and lighting to improve energy efficiency and reduce costs. The most common energy simulation software tools for the building include EnergyPlus [56], IESVE [127], and eQUEST [71]. Attia et al. [19] also conducted a comparative analysis of ten common energy simulation tools that are typically used in the early design stages of buildings. Project management software is used to manage the building design process from start to finish. This software allows project managers to create schedules, assign tasks, and track progress, ensuring that projects are completed on time and within budget. Other analysis software is also used to assess and optimize various aspects of building design, such as structural analysis, acoustics, and lighting. However, there are limitations in existing software tools. One major issue is their complexity, which can require significant training and expertise to use effectively, making them inaccessible to small firms or individual designers. Integration issues can also arise when working with different software tools, leading to errors and inconsistencies when data is manually transferred between software. The accuracy of simulation software can also be limited by incomplete or inaccurate data. Despite these challenges, software tools remain essential for creating high-quality, efficient, and cost-effective building designs. By leveraging these tools, designers can improve collaboration and communication among team members, streamline workflows, and ultimately create better building designs.

Negative Impacts of Poor Building Design

Poor building design can have significant negative impacts on the building occupants, the environment, and the economy. One of the most immediate and visible consequences of poor building design is the impact on occupants' health and comfort [170, 74, 33, 32]. Poor ventilation, lighting, acoustics, and thermal comfort can all contribute to health problems such as allergies, asthma, headaches, and stress. These problems can lead to decreased productivity and reduced quality of life for building occupants. Another negative impact of poor building design is its effect on the environment. Buildings are responsible for more than 40% of energy consumption worldwide [4] and 40% of total global Greenhouse Gas (GHG) emissions from operations and the manufacture of building materials [106], and poor design can exacerbate these problems [53]. For example, buildings that are poorly insulated, have inefficient heating and cooling systems, or use energy-intensive materials can contribute to higher energy consumption and carbon emissions. Another example is that the HVAC system in a building is often oversized due to design safety factors and a lack of accurate building load calculations [63]. This not only contributes to global climate change but can also lead to higher energy costs for building owners and occupants. Lastly, poor building design can have negative economic impacts [194]. Inefficient buildings can lead to higher energy bills and maintenance costs, reducing the economic value of the building. Poor building design can have far-reaching negative impacts on human health and comfort, the environment, and the economy. It is essential to prioritize good design practices, including the incorporation of automation tools, to create buildings that are efficient, sustainable, and safe for their occupants.

2.4 Electronic Design Automation

While looking at the present status of the design workflow for buildings, it is instructive to compare it to that of the Electronic Design Automation (EDA) referring to the use of software tools and algorithms to automate various aspects of designing and manufacturing complex electronic components, including today's state of the art Integrated Circuits (ICs). EDA involves the use of computer programs that assist designers in creating, verifying, and testing electronic systems, ranging from individual circuits to complex integrated circuits and systems. Design automation aims to improve the efficiency and productivity of the design process by reducing the time and effort required for manual tasks and by enabling designers to explore more design options and trade-offs in a shorter amount of time. The following section describes the design process of electronics, the evolution of the EDA, and the current state of EDA and its impact.

Electronic Design Workflow

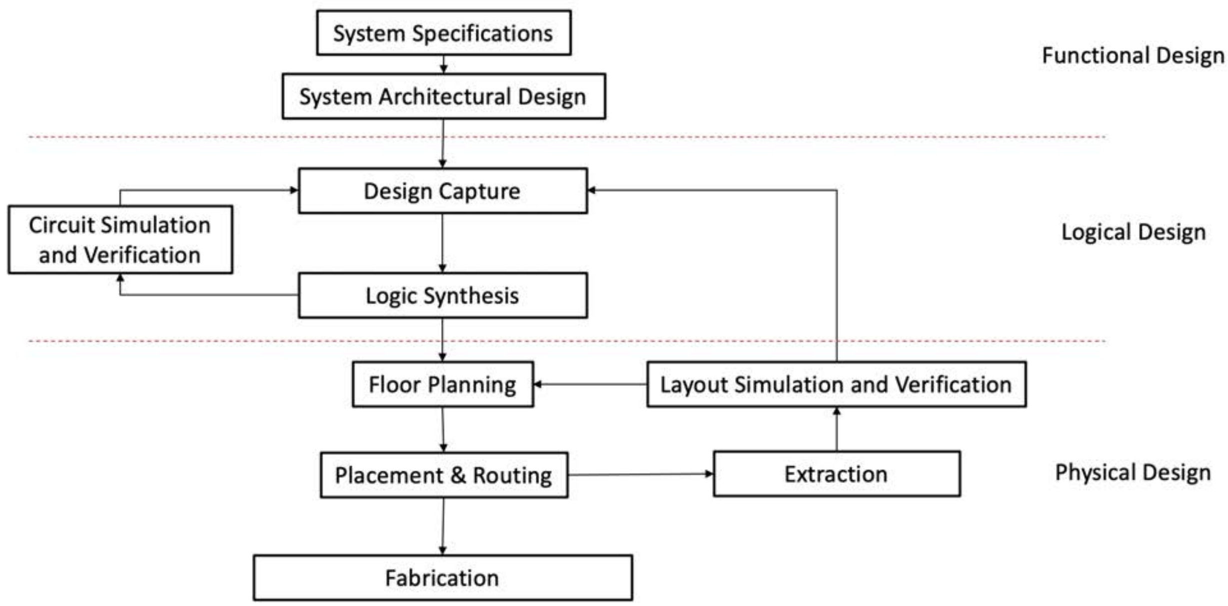

Figure 2.2: Electronic Design Workflow

The process of electronic design can vary depending on the project size and specifications, but generally, for an IC, it follows a top-down design process [35] as shown in figure 2.2. The first step is to define the system specifications, which include the desired performance, functionality, and power consumption of the system. Based on these specifications, a high-level block diagram is created to define the system-level architecture and interconnections between the functional components. Once the architecture is defined, the next step is design capture, which involves creating a high-level design description of the system using a Hardware Description Language (HDL). This is followed by logic synthesis, where the captured design is transformed into a gate-level netlist that describes the circuit's logic in terms of logical gates, flip-flops, and other standard cells. Next, circuit simulation and verification are performed to verify the circuit's functionality. This can involve some iterations to make sure that the simulated results meet the desired specifications. The next level of design is the physical design. Floor planning involves determining the physical location of the various functional blocks in the design. The placement and routing step follows where the physical locations of individual gates and components are determined and the connections between them are established by routing wires. After placement and routing, the circuit layout is extracted and used for simulation and verification. This involves ensuring that the physical layout matches the intended design and verifying the functionality and performance of the circuit. Any issues found during this step may require adjustments to the design, placement, or routing before final verification and fabrication. Lastly, the design is ready for fabrication, where it is physically manufactured using the digital description of the final design. The above process emphasizes that electronic design is an iterative, yet highly streamlined process aimed at ensuring that the functionality meets the desired specifications. Moreover, each design phase represents a distinct and well defined level of abstraction, enabling effective analysis.

As technology continues to advance, electronic design has become more complex, resulting in the emergence of new design protocols. One such process is the System on a Chip (SoC) design [139], which involves integrating multiple components onto a single chip. This process requires specialized design tools and methodologies, including co-design, Intellectual Property (IP) reuse, and system-level verification, to ensure that the individual components work together effectively. Another emerging design process is 3D IC design [117], which involves stacking multiple layers of chips vertically to increase performance and reduce size. This process involves several new challenges, including thermal management, power distribution, and signal integrity. However, for the purpose of this paper, we will mainly focus on the top-down approach in electronic design, which is more similar to the current building design process.

Evolution of EDA

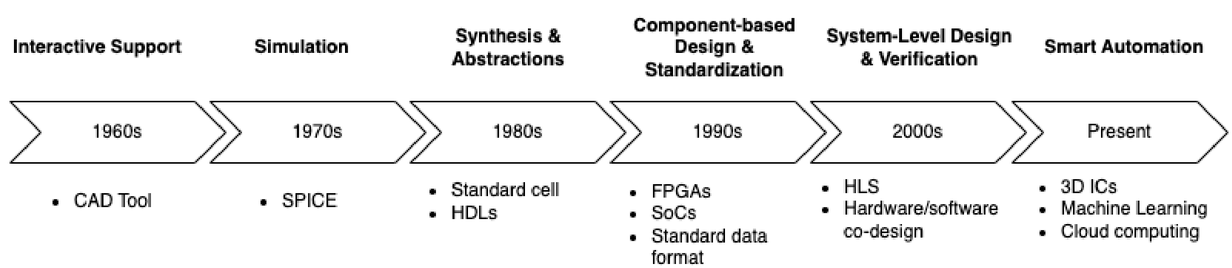

Figure 2.3: Timeline of Key Developments of EDA

EDA has a significant impact on the semiconductor industry by enabling faster, more efficient, and more reliable designs of electronic systems. EDA tools provide designers with a range of features and capabilities that simplify and automate the design process, enabling them to create complex designs more quickly and accurately. Fig 2.3 shows the timeline of key developments of EDA from interactive design support to design automation. The development of EDA tools began in the 1960s when researchers developed the first CAD tools [178] designed to assist engineers in analyzing and designing circuits and boards. It transits from a traditional hand-drawn design to a digital design. Later, Simulation Program with Integrated Circuit Emphasis (SPICE) emerged in the early 1970s [191] as a student project, but became an industry standard simulation software for IC Design.

In the late 1970s and early 1980s, two major technologies emerged: standard cell design and HDL [165]. The concept of standard cells involves pre-designed circuit blocks that contain a specific logic function, such as an AND gate or a flip-flop. These standard cells can be combined to create more complex circuits. The introduction of standard cells separates the transistor-level design from the logic design. On the other hand, HDLs, such as VHDL and Verilog, provide a high-level language for describing digital circuits, enabling designers to specify the behavior of a circuit without having to worry about the details of the underlying hardware.

In the 1990s, EDA tools continued to evolve, with the introduction of new tools and methodologies such as Field Programmable Gate Array (FPGA) [120] and SoC design [139]. FPGAs were programmable devices that could be used to implement custom logic functions, while SoC design involved the integration of multiple functions onto a single chip. Furthermore, the industry developed standard ASCII formats, Library Exchange Format (LEF) and Data Exchange Format (DEF) [37], for representing library and design data in order to share and reuse design data across different tools and platforms.

In the 2000s, High-Level Synthesis (HLS) and hardware/software co-design are introduced. HLS allowed designers to describe hardware using a high-level programming language, which could then be synthesized into hardware. Hardware/software co-design involved the simultaneous design of hardware and software components, enabling the design of more complex systems that integrated both hardware and software.

Current State of EDA and its Impact

The current state-of-the-art in EDA includes advanced technologies that enable designers to create complex semiconductor chips with high performance, high reliability, and low power consumption. HLS technology [84] allows designers to specify chip functionality at a higher level of abstraction, which reduces the time and effort required for manual coding. Machine learning methods [105] are also applied in EDA industry to optimize design parameters to further improve design quality. Furthermore, cloud computing [36] allows designers to access on-demand computing resources to perform tasks that required high computational power without having to invest in expensive hardware and software infrastructure. Advanced verification and validation techniques [65], such as formal verification, simulation, and emulation ensured the reliability and correctness of complex designs. Lastly, as chips become smaller and more complex, the placement and routing of components on the chip become more challenging for EDA tools. As a result, placing and routing algorithms [164] are constantly evolving to incorporate new design methodologies that can help designers to optimize chip layouts for power, performance, and manufacturability.

Automation is necessary to handle the immense complexity of semiconductor chips, which can have over a billion circuit elements that can interact in subtle ways. Manufacturing variations can introduce further complexities and changes in circuit behavior. Errors in manufactured chips can be disastrous and often cannot be fixed. Re-designing and Re-manufacturing the entire chip is time-consuming and expensive, which can lead to project failure. EDA technology provides the critical automation needed to manage the complexity, making it possible to design and manufacture modern semiconductor devices with a high level of accuracy and efficiency.

2.5 Comparison between EDA and the current Building Design Process

While the current building industry has yet to reach a high threshold for design automation, we can learn from the development of EDA to identify the key aspects needed to make it a reality. Figure 2.4 outlines the comparison between electronic design and building design. We will examine three key aspects: design process, design tools, and industry, and compare the similarities and differences between them in greater detail in the following sections.

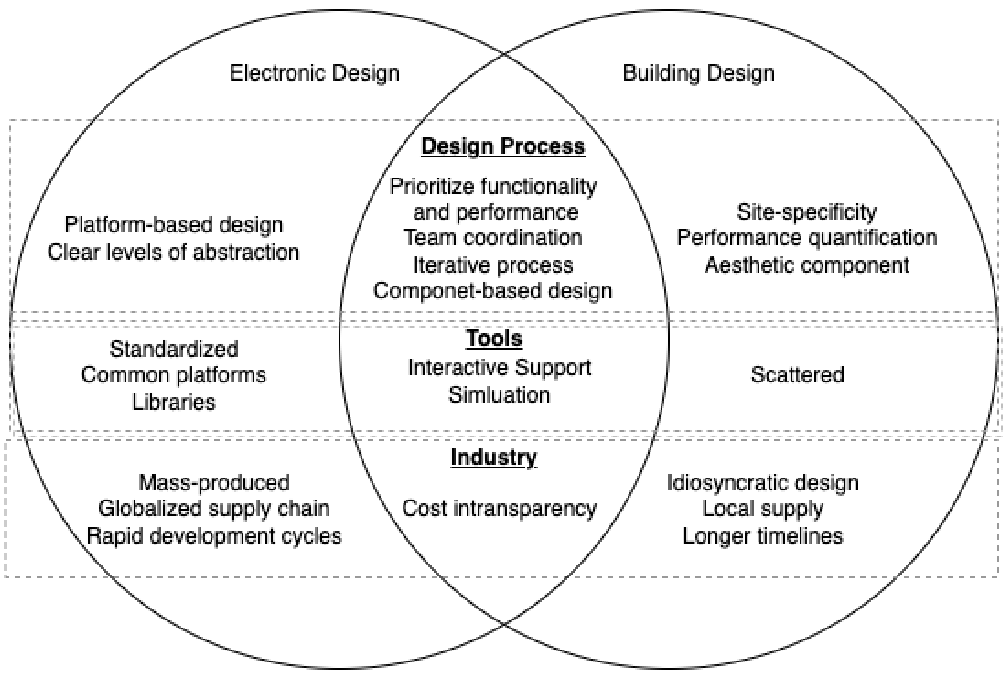

Figure 2.4: Comparison between electronic design and building design.

Design process

Both electronic design and building design begin with specifying the project requirements and constraints, which usually include functionality and performance. Additionally, both processes involve the contribution of multiple team players to complete the design. In electronic design, this may include designers, engineers, and other specialists, while building design usually involves architects, engineers, consultants, contractors, and constructors. Effective collaboration among stakeholders is essential for achieving an optimal design. Both processes are iterative, where certain stages are repeated until the optimal design is achieved. The iterative process allows designers to refine and optimize the design over time, making adjustments to accommodate changing requirements or constraints. This also helps identify potential issues early on, reducing the risk of errors in later stages of the design. Furthermore, both design processes involve component-based design, where components are selected and integrated into the design as a whole. In building design, this includes various building components, such as walls, windows, doors, and HVAC components, while in electronic design, it involves components such as sensors and devices depending on the level of abstraction.

However, building design often employs a component-based design approach at the subsystem level, such as for HVAC system or structural component design. This approach is rarely available at the system level, primarily due to the lack of a common platform in the building design domain. Design and simulation tools used in building design are often incompatible with each other, making it difficult to integrate designs into a single platform. This lack of integration can lead to errors, duplication of effort, and increased design time. The current efforts in BIM have helped to address some of these challenges by providing a platform for integrating various building design tools and facilitating the exchange of information between stakeholders. However, there are still limitations in software compatibility and data management. Furthermore, the lack of clear definitions for different development objectives and levels of abstractions during different design stages can further complicate the design process. In contrast, the electronic industry benefits from clear and standardized input-output requirements.

The existing Level of Detail (LoD) framework of BIM developed by the American Institute of Architects (AIA) [14] is defined in Table 2.1.

Table 2.1: The LoD for BIM [14].

LoD	**Model Descriptions**
LoD 100	Approximate graphical representation of the entire building based on spatial requirements
LoD 200	Determine approximate floor plans and space boundaries (walls, elevation, and columns)
LoD 300	Detailed design for actual construction
LoD 400	Precise model for fabrication, structure, electrical, mechanical, and plumbing systems
LoD 500	Complete design, which represents the actual building

LoD defines the amount and degree of building information that needs to be in the BIM at different stages. It is developed for construction purposes and is not directly applicable to all disciplines during the design stages. The broad definition requires elaboration to fit into design purposes to allow the development of design automation in the building industry. The building design is often limited by site-specificity, which can make it difficult to develop a clear design process. Each building project has unique site requirements, such as topography, climate, and local regulations. These factors can have a significant impact on the design decisions and may require adjustments to the design throughout the process. As a result, the design process in building design can be more complex and time-consuming than in electronic design, where products can be developed independently at a specific site.

Another difference in the design process between electronics and buildings is the performance quantification aspect. In electronic design, the performance metrics can be easily obtained through calculations in timing and energy performance. However, in the building industry, several aspects need to be considered, such as energy efficiency, indoor air quality, visual comfort, thermal comfort, acoustic lighting, and water efficiency. These aspects are not always straightforward to quantify, resulting in discrepancies among designers. Additionally, due to various constraints, design trade-offs become more complex and harder to make in building design.

Lastly, the level of attention to the occupant experience and the important of aesthetics of building design are vastly different from electronic design. Unlike electronic design, building design has to take into account the physical environment and how the building will fit into the surrounding landscape. Designers have to consider the impact of the building on the environment, the local culture, and the community it will serve. In contrast, electronic design focuses almost entirely on functionality and efficiency. While the aesthetic portion of building design is challenging to fit into design automation applications, other areas such as structural design and construction planning can benefit greatly from automation.

Design Tools

CAD and simulation tools are commonly used in both electronic design and building design. These tools can provide interactive support and simulation capabilities to help designers explore design options, identify potential problems, and optimize design solutions.

In electronic design, simulation tools are highly standardized, with well-established input-output relationships that enable designers to quickly and easily model electronic circuits, test different design scenarios, and verify design performance. There is also a common platform for simulation tools, which allows designers to use different simulation tools with similar syntax, enabling the transfer of simulation models between different software programs.

In contrast, building design lacks a universal standard for simulation tools, which can make it challenging for designers to choose the right tool for their specific design problem. Energy simulation software, for example, may require different inputs for different programs, making it difficult to have a common platform for simulation tools. Furthermore, there are limited data standards that cover all simulation tools, and data conversion between tools often requires manual adjustment. Building designers or engineers often need to adapt to different software programs, such as structure, energy, and lighting simulations, for different design purposes, which results in a fragmented design process. Interoperability is a widely known issue in the building industry [104]. Data standards, such as Industry Foundation Classes (IFC) [107] and Green Building XML (gbXML) [86], exist in the building industry. IFC is used to exchange building data, including geometry, spatial elements, and sensor information. A subset of IFC, Model View Definition (MVD), has been developed to apply to specific applications in building [102]. It defines which IFC entities, attributes, and relationships are required to support a specific use case or task. The gbXML format is more specifically used in the energy simulation domain. It facilitates the exchange of data between CAD and energy analysis tools. Other data tools in the building industry are summarized in [135]. However, the above-mentioned data standards have yet to be applied to all building applications. Extensions or adaptations are still required to apply to specific building applications or regions [82].

On the other hand, electronic data standards, LEF and DEF [37], are well-established in exchanging data between different software programs. LEF is used to exchange library data, while DEF is used to exchange design data. Building data standards need to have broad adoption across the industry and cover all relevant disciplines. Different from LEF and DEF, it needs to be designed to be flexible and adaptable to different use cases and applications in building. Moreover, a library data standard needs to exist to store different application modules within the building industry. Its primary purpose is to enable seamless data exchange between different software applications used in building design, construction, and operation. By doing so, it enables the industry to create a shared library that allows for efficient sharing and reusing of data for future design processes.

In addition to the challenges of standardization and interoperability, another pivotal issue in building design is maintaining up-to-date, high-quality data throughout the design process and among stakeholders. Failure to keep data updated can result in miscommunication, additional time required, and increased costs. Having the data updated is especially important during the construction process, where delays and errors can have significant impacts on project time and costs [216]. Therefore, having an efficient and effective data management system is also vital for building design.

A comparison between the Building and the Electronics Industries

In building design, it can be challenging to estimate project costs upfront, which can lead to difficulties in accurately estimating the overall project cost. The cost is determined through a construction bidding process. As a result, the cost of sub-systems is usually not publicly available. Several researchers have explored various methods to improve cost estimation in the building industry [103], including the use of historical cost data and cost modeling techniques. Similarly, in the electronic industry, cost estimation is also challenging due to the competitive nature of the industry. For in-house manufacturing products, the cost is generally easier to estimate because the manufacturing process is known and predictable. On the other hand, the cost of custom chip designs that are outsourced for manufacturing can be more challenging to estimate, as it may depend on factors such as the complexity of the design, the choice of manufacturing partners, and the timing of the project.

One major difference between the two industries is the nature of the products produced. Electronic design often involves mass-produced products, while building design usually involves idiosyncratic designs. In electronic design, products are typically manufactured in large quantities, with standardized components and design processes, which can lead to more streamlined production and lower costs. Building design, on the other hand, is often unique to each project and requires more customized solutions. As a result, the design process needs to be flexible to accommodate a wide range of project types and requirements.

There is also a notable difference in the scale and timeline of outcomes between electronic design and building design. In electronic design, products are often smaller in scale and require shorter development cycles due to the nature of the industry. This allows for rapid prototyping, testing, and production, which can result in more agile and iterative design processes. On the other hand, building design projects involve larger-scale outcomes that often require longer timelines due to the complex nature of the construction process. This can result in a less agile design process, with greater risks and costs associated with design changes over time.

Another significant difference is the supply chain. The electronic design industry often relies on a global supply chain, with components sourced from all over the world. In contrast, the building design industry tends to rely more on local suppliers and materials, which can vary depending on the region or location of the project. Although building elements, such as raw materials, prefabricated components, and equipment, can be sourced globally, local supply sources are often preferred for their positive impact on the environment and economy. This can influence factors such as availability, cost, and quality of materials, as well as the overall design and construction process.

2.6 Module-based Building Design

In this section, we propose a modular design flow that segregates various disciplines in building design into separate modules, aimed at facilitating the development of libraries and enabling design automation.

The building design process is generally split into five different design stages: concept, schematic design, design development, construction documents, and construction. However, no clear objectives are defined at each stage. The ambiguity in defining different stages of building design arises from a lack of standardization, variation in project scope and complexity, and overlapping and iterative nature of the design process. Due to the ambiguous definitions and varying inputs and outputs across different research groups, research in different disciplines of building design has become fragmented, making it difficult to integrate research into current industry practices. Identifying the gaps between research and the building industry is therefore essential to bring them closer together and bridge the divide. Our aim is to minimize these gaps and facilitate the transfer of knowledge and research findings to the industry.

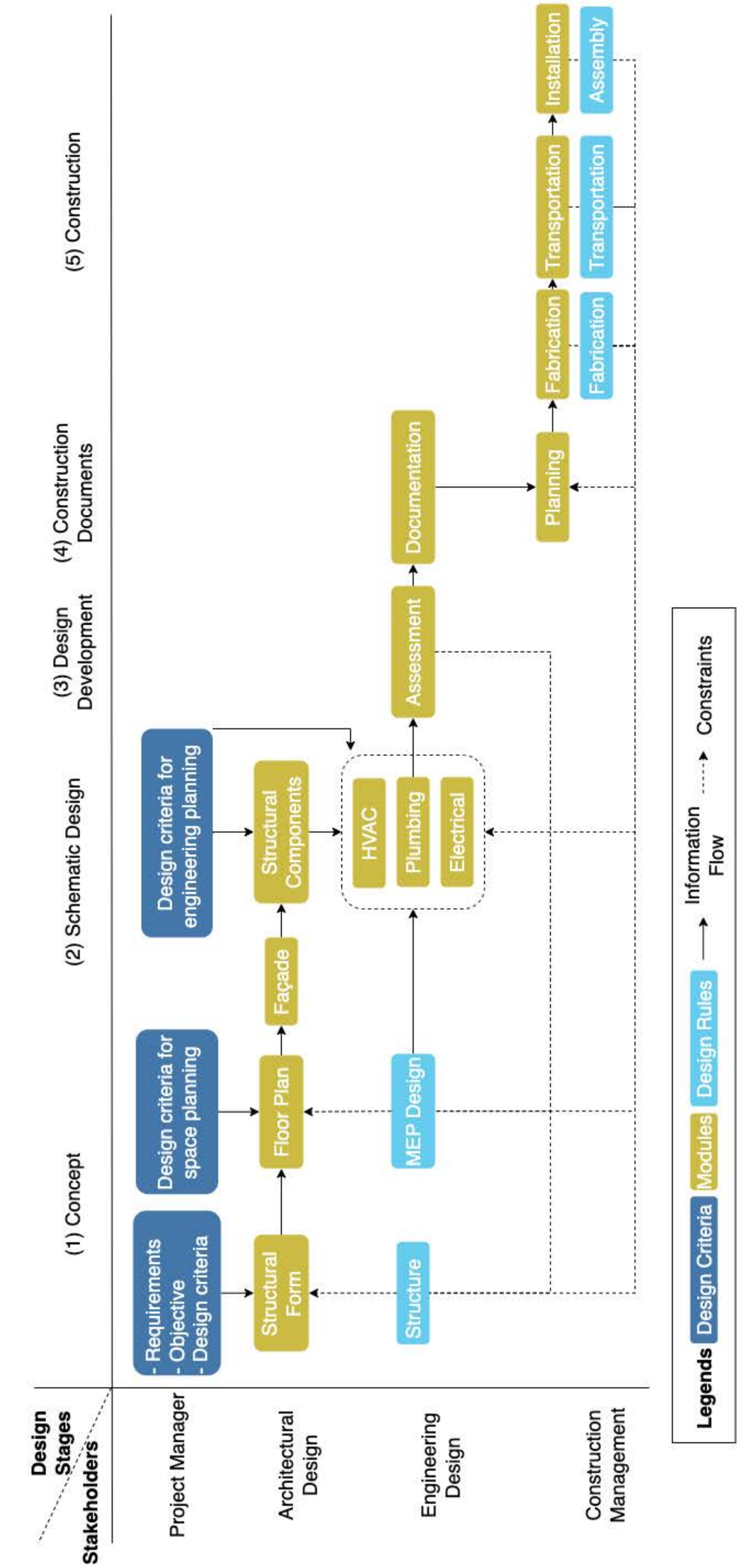

Figure 2.5: Proposed module-based approach for design automation in the building design process.

Fig 2.5 describes the proposed module-based approach of the design process that integrates design automation techniques of different disciplines into a design flow. Different disciplines of the building design process are split into different modules: structural form, floor plan, façade, structural components, HVAC, electrical, plumbing, assessment, documentation, planning, fabrication, transportation, and installation. Each module contains design automation methods with specific input-output specifications as shown in Table 2.2 and 2.3. The objective is not to create a comprehensive review of design automation studies, but to offer instances of commonly employed techniques in research communities. Modules are connected to one another to demonstrate the design sequence and they are bounded by design rules. The design rules are generally established through physical constraints, building codes, safety standards, environmental regulations, and budget constraints.

The building design process commences by creating the structural form of the building based on client requirements, building objectives, and design criteria for the site, while adhering to structural constraints and energy building codes. Then, the floor plan is developed by integrating inputs from the structural form and space planning design criteria. However, it is subject to MEP design rules to ensure sufficient space for MEP equipment. Following the floor plan is designed, façade and structural components are determined to finalize the architectural design of the building. Subsequently, HVAC, electrical, and plumbing systems are designed in a coordinated manner to meet the occupants' needs and spatial requirements. Once the MEP system is in place, an assessment module performs a final check of the building code before creating the construction documents. The construction planning module then facilitates planning for fabrication, transportation, and installation during the construction stage. Lastly, those modules in the construction stage implement the construction plan to complete the building design.

Although the figure shows that the modules are linked, there is still a discrepancy between the outputs of one module and the inputs of the connected module. Currently, the linked connection requires manual intervention to ensure a proper information flow between modules, and the backbone of the information flow is BIM. Several researchers have been working on extending the data structure, such as IFC [107], to fit different applications' needs [82]. However, the current data structure still hasn't addressed design automation applications completely. Additionally, the proposed design flow is not a single iteration process from left to right. Revisions or adjustments from previous modules may be necessary to ensure compatibility and proper functioning of the overall system. However, over time, design rules can be expanded by incorporating feedback from professional experts and by collecting more data and information to better address the needs and constraints of the project. They can facilitate reducing the number of iterations needed to create an optimal building design. Lastly, the proposed approach is not intended to replace architects and engineers completely, but rather, to offer design suggestions and enhance communication between designers and engineers during the design process.

The design process is designed to be flexible to accommodate regional, climatic, and firm-specific variations in the building design process. Furthermore, the design process encourages researchers to reconsider the necessity of standardizing information flow between different disciplines, allowing designers to easily compare and contrast the results of various methods.

2.7 Platform-based Building Design

In the previous section, we provided an overview of the building design flow at a higher level. In this section, we delve into a more detailed view on how each module can be implemented using Platform-based Design (PBD) methodology. PBD [78] refers to an approach in the design paradigm where a common base or platform is used as a foundation for creating multiple variations or derivatives of a design. It emphasizes the reuse of components across different designs, allowing for faster and more efficient product development. While EDA is a prime example, PBD has also been successfully applied in other industries, including automotive [169], aerospace [25], and healthcare [207]. In PBD, a *platform* is defined as a collection of components and their accompanying rules for combining them, which can be utilized to create a design at a specific level of abstraction. Jia et al. [110] proposed a PBD approach specifically tailored for smart building design. The approach focuses on promoting the reuse of hardware and software components on shared infrastructures. They present a case study of retrofitting the HVAC system in a smart building by deploying sensors and actuators to enhance energy efficiency and occupants' comfort. The PBD approach enables the reuse of sensors and actuators across different smart building designs, leading to more cost-effective and sustainable solutions. We follow a similar approach, but instead of applying to building retrofit applications, we apply the technique to building design, specifically for the HVAC systems.

A new Workflow for Building Design

The approach follows closely to the design flow developed from [110], with the adaptations to suit the building design process. The concept is to begin with high-level design specifications and gradually refine the model in subsequent steps, leading to the implementation of the design at different levels of abstraction. This design flow does not strictly follow a top-down or bottom-up approach, but instead adopts a meet-in-the-middle approach that combines elements of both processes. The bottom-up approach begins with detailed components or subsystems and builds up to a higher-level design.

The design flow is a multi-layered process that involves the functional design layer, the module design layer, and the implementation design layer, as depicted in Figure 2.6. Each layer is accompanied by corresponding libraries that aid in the design process. The libraries that correspond to each layer are a virtual design platform, a module platform, and an implementation platform, respectively.

The virtual design platform is composed of several components, including design templates and generative algorithms. Design templates are created based on building codes or previous building projects, and provide a suggested layout for a specific design specification. On the other hand, generative algorithms utilize AI to generate alternative design sugges-

Table 2.2: Architectural Design Modules

Module		**Behavioral Model**		**Extra-Functional Model**
object	*Method*	*Inputs*	*Outputs*	*Objective*
Structural Form	CAD/E [210]	Design objectives and constraints	Building forms	N/A
	GD [197]	Building outline, loading, span	Structure model of steel framing systems and structural material quantities	Embodied Carbon
	GA [209]	Building size	Building forms	Energy performance
Floor Plan	Physically based [12]	Spaces and shape	Space topology	Adjacency, separation, orientation, alignment, area, proportion
	Evolution Algorithm [202]	Floor area, room ratios, adjacency preference matrix	Space topology	Budget, adjacency preferences and space function
	Agent-based modeling, SA [77]	Simulated occupants' behavior	Space layout	Mobility, accessibility, and coziness
	Agent-based modeling, Linear/Quadratic Programming [29]	Building spaces	Optimal assignment of building spaces	Occupants' flow, satisfaction, and energy efficiency
Façade	Parametric Model [193]	Building geometry	U-values of façades	Thermal comfort and energy savings
	GA [184]	Geometric parameters	Parameters' value	Daylight performance
	GAN [145]	existing facçade design images	facçade design	N/A
Structural Components	Knowledge-based Method [85]	Building structure	Detailed design of structural components	N/A
	Neural Network [1]	Loading condition	Cross-sectional areas of trusses	Material weight
	SA [27]	Loading condition	Cross-sectional areas of trusses	Material Weight
	GA [40]	Building structure	Construction materials properties	Thermal and lighting performance

Table 2.3: Engineering and Construction Design Modules

Module		**Behavioral Model**		**Extra-Functional Model**
object	*Method*	*Inputs*	*Outputs*	*Objective*
HVAC	Physics-based (BPS) [24]	Building structure and layout	duct and radiant systems placement	Cost, GHG emissions, life-cycle
	GA [215]	Building structure and layout	HVAC component selections and topology	Energy efficiency
Assessment	Rule-based [13]	BIM	Report documents	Green building assessment
Planning	Computer Integral Manufacturing [149]	BIM	Off-site prefabrication plan	Time, transportation, market, legal, economic
	Mixed-Integer Programming [11]	BIM	Transportation plan (Truck assignment and delivery day)	Cost
	Imaged-based 3D modeling [61]	BIM, robot property, task	Assembly plan	Time
Data Collection	UAV/UGV [16]	Construction site	Construction environment map	Surveying, monitoring, and inspection
	RF/RFID [144]	Construction site	Labor locations	Project performance
	Positioning sensors [50]	Construction site	Dynamic resources quantities	Real-time resource availability
	3D laser scanning [10]	Construction site	3D point clouds	Quality Control

tions based on the input data and specification. The libraries enable designers to explore various design options and select the most suitable one based on the specifications, thus enabling them to advance to the next level of abstraction. The functional design layer yields the topology prototype design, which depicts the interconnections between different components. Subsequently, the module design layer comprises component and simulation modules. This layer facilitates designers to experiment with different components and conduct simulation studies to evaluate hypothetical scenarios of the resulting design. The outcome of this layer is a 3D Prototype design, which is a more detailed representation design. In the implementation platform, the design undergoes verification and documentation processes using verification and documentation modules. These modules aid in verifying the design's functionality and producing documentation to describe the design's specifications.

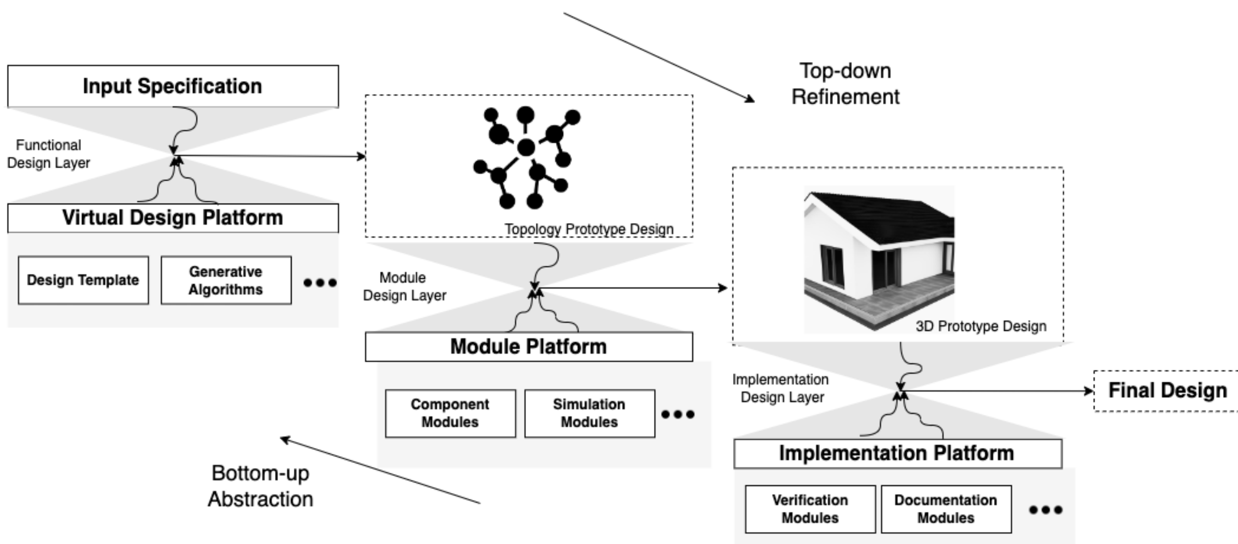

Figure 2.6: An overview of the proposed design flow adapted from [110].

Platform-based Building Design Case Study

We present a case study to demonstrate the practical application of the PBD framework in the design of HVAC systems for a building. Assuming we are given a BIM that contains building form and floor plan information, the design specification consists of the desired design cost, comfort requirements, and maximum energy consumption value.

In the functional design layer, the HVAC configuration templates developed by ASHRAE [154] are utilized to match the design specifications. These templates are selected based on the building type and typical heat load of the zones and the building. Although researchers have attempted to develop new HVAC topologies using GA, Zhang et al. [215] found that the existing configurations still outperform the new generative alternatives. However, if future generative studies succeed in outperforming the existing configurations, they can be stored in the virtual design platform. Once the appropriate configurations are selected, the component modules stored in the module platform are used to select the best-suited components for the design. Additionally, 2D topology is converted to 3D by applying duct layout modules that fit the air ducting system to the building floor plan. The resulting design is then sent to the implementation layer for implementation. The implementation layer consists of a final verification stage, where the design is checked for compliance with building codes and feasibility for implementation. Once validated, the documentation module is used to generate the final construction documents required for bidding purposes.

2.8 Chapter Summary

Buildings are complicated systems that consist of different layers of sub-systems. In addition, decisions made in the early stages of building projects have an important impact on material and energy efficiency. It is a challenging task to frame and solve one multi-objective optimization problem for finding an optimal design solution for a building. There is a need to develop a standardized information flow specifically for different disciplines. This chapter identifies the shortcomings in the building design process and proposes a modular-based and a PBD approaches.

Despite ongoing research efforts to streamline the building design process, the industry has been slow to adopt new technologies and approaches. One of the key obstacles to widespread adoption is the lack of a universally defined design workflow in the industry. Building design practices can vary significantly based on factors such as location, building type, and project scope, making it challenging for companies to invest in optimization and co-optimization techniques during the design phase. Many optimization techniques may not be applicable to all projects, leading to concerns about cost-effectiveness and return on investment.

To overcome this challenge, the industry may need to focus on developing more standardized approaches to building design, with greater emphasis on collaboration and knowledge-sharing among stakeholders. This could include the development of a platform-based or modular-based approach that is flexible and adaptable to different project types and scopes. Modularization involves dividing buildings into assemblies of components that have standardized interfaces for communication, making it possible to combine and reconfigure components to meet different design requirements. This allows for a more flexible design to meet users' preferences and performance requirements. This approach offers several benefits, including greater flexibility in design, more efficient use of resources, and improved cost-effectiveness.

Additionally, to facilitate more efficient and collaborative building design, it is necessary to create a design backbone that enables single-platform integration. First, data exchange standards should be revised to ensure they are applicable to all disciplines involved in building design. This will help ensure that information can flow smoothly between different software applications and enable effective collaboration. Next, a BIM software, such as Revit, can be

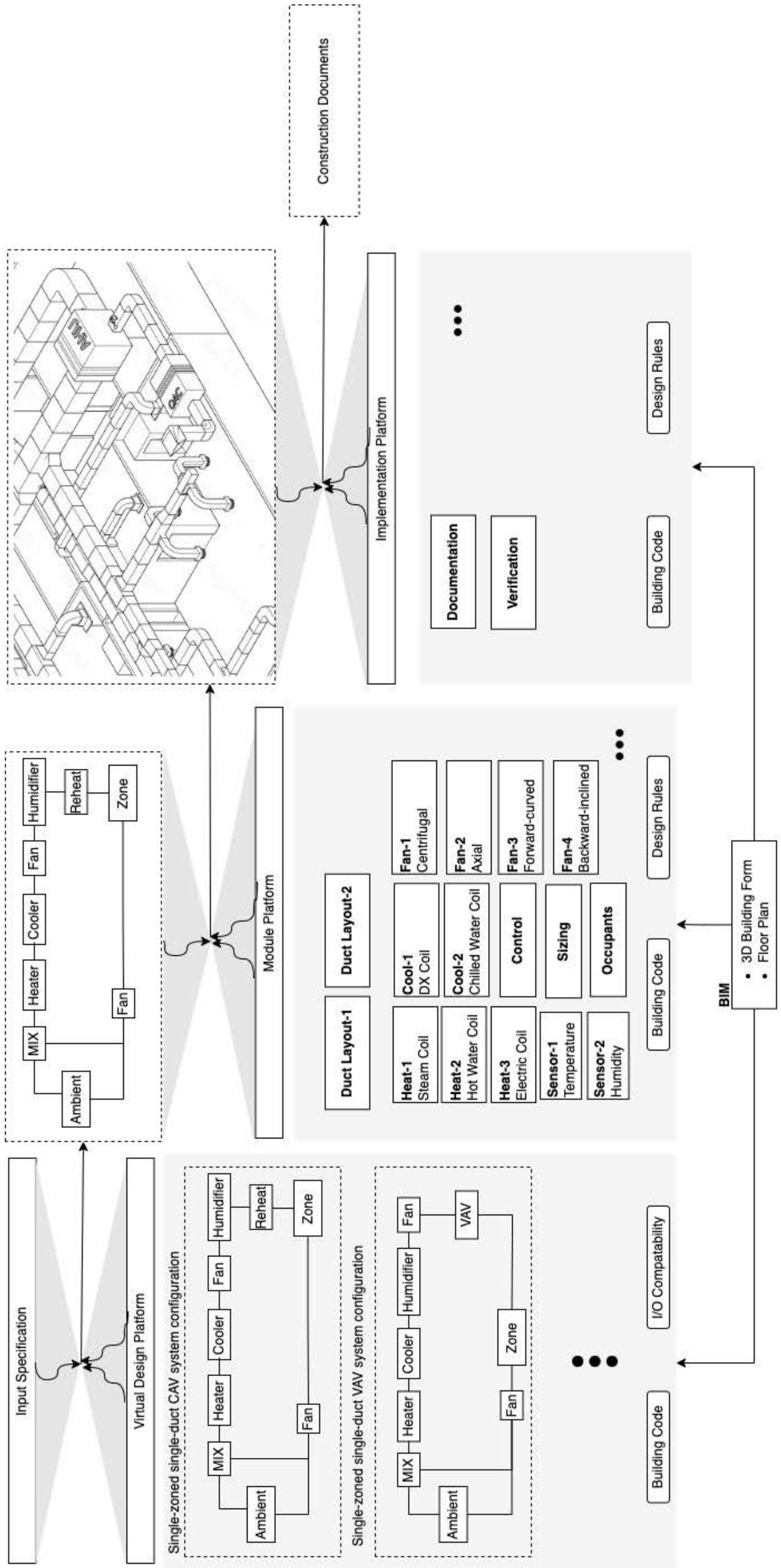

Figure 2.7: A detailed overview of the PBD design flow of an HVAC system.

used as a common platform for communication between different software tools. By integrating all existing software tools into the BIM software through support plug-in application modules, designers can access all the necessary information in one place, improving efficiency and reducing errors.

Building design requires a more comprehensive approach that considers several aspects of performance, including energy efficiency, indoor air quality, visual comfort, thermal comfort, acoustic lighting, and water efficiency. There is a need to define and standardize a performance quantification framework for each aspect of concern in the building industry. While building codes and standards exist to facilitate better building designs, there is still a lack of a comprehensive framework in certain areas, such as visual comfort. Ongoing efforts are made in the research domain. For example, Cavieres [43] established a framework that allows the functional and behavioral systems of the building to interact in an interface. This framework involves mapping the specific systems needed to calculate the relevant performance measures, which in turn helps designers make more informed design choices. By quantifying and standardizing various aspects of building performance, designers can better understand the trade-offs between different design options.

Lastly, risk assessment is another important aspect to address in building design. Although innovative designs can lead to reduced energy consumption and GHG emissions, there is no guarantee that the desired outcomes will be achieved during construction. If the design conditions cannot be met, construction costs can increase significantly, and contractors may be unwilling to take on the project. A risk assessment module can help mitigate these risks by simulating various design scenarios and estimating the uncertainty associated with each design. This will allow stakeholders to make informed decisions and select designs that are more likely to succeed in the construction phase.

The implementation of standardization, performance quantification, and risk assessment modules is necessary to move building design toward automation. Standardization promotes a more structured approach to building design, allowing for better data exchange and knowledge-sharing between stakeholders. By implementing performance quantification frameworks, designers can make more informed decisions regarding various aspects of building design. Risk assessment can help mitigate potential issues during the design process, preventing costly and time-consuming delays during construction. The use of these tools not only streamlines the design process but also leads to more sustainable building designs that meet performance and safety standards. The ultimate goal is partial design automation, where designers and engineers can leverage technology to optimize building performance and minimize the environmental impact.

Chapter 3

Defining Levels of Abstraction for Building Energy Models[1]

3.1 Background

Building models are designed to emulate actual physical buildings that serve various applications, including design [150], indoor environment quality assessment and control [100, 115], Heating, Ventilation, and Air-Conditioning (HVAC) control [26], diagnosis [140, 217], and demand response [119]. They aim to reduce building energy consumption, maintain occupants' comfort, correctly size the HVAC, and provide services to the power grid. Building Performance Simulation (BPS) tools were initially developed in the 1970s to help make better design choices during the design phase of a building [121]. The objective of simulation models in the design phase is to optimize performance requirements through optimal choices for various design parameters, such as construction materials, shading strategies, zone layout, and plant sizing. Research shows that better design for new buildings may result in substantial energy savings [53]. With BPS tools, designers can better understand hypothetical scenarios when selecting different design options. In addition, they have the potential to identify imperceptible internal system problems, such as poor indoor air quality and structural cracks. In recent decades, BPS tools have also been used to monitor and improve building operations.

However, BPS tools are often not carried over from the design phase to the operation phase. The challenges in building modeling include the performance gap between the estimated building performance in the design stage and the actual performance during the operation stage and the interoperability between different simulation tools [104]. Two ways to address the challenges are to define the levels of abstraction of building models from the design phase to the building operation phase and establish a communication standard between Building Information Modeling (BIM) and BPS tools. BIM is a digital representation

[1]This chapter is a modified version of a manuscript that is preparing for submission with the preprint available in reference [129].

of a building that contains information such as the building's geometry, structure, materials, HVAC, lighting, plumbing, and electrical systems [113].

Defining a clear level of abstraction for building models can provide a structured approach to developing building models and facilitate automation in building model generation. The level of abstraction refers to the amount of complexity with which a system is viewed or programmed. Higher levels of abstraction involve less detail, while lower levels involve more detail. This concept is illustrated in integrated circuit design, where different levels of detail, from less detailed to more detailed, are used, such as system level, chip level, register level, gate level, circuit level, and layout level [199]. By defining the levels of abstraction for building models, designers can establish a systematic approach to model development, allowing for consistency and efficiency in the modeling process. This can aid in automating certain aspects of building modeling, leading to faster and more accurate model generation. Clear deliverables at each level of abstraction can also help establish responsibilities for designers at different stages of the design process, ensuring that the appropriate level of detail is considered at each stage.

In addition to defining the level of abstraction, interoperability between BPS tools is important. There are numerous BPS tools available, each with its own strengths and capabilities for building modeling. However, there is often a need for manual conversion of information between different tools, which can be time-consuming and error-prone. Although data exchange standards such as Industry Foundation Classes (IFC) [107] and Green Building XML (gbXML) [86] exist, they may not be widely applicable to all BPS tools, and information loss may occur during the data exchange process. Efforts towards improving interoperability between BPS tools can lead to more seamless data exchange, allowing for smoother integration of different modeling approaches and tools.

This chapter aims to address the crucial role of BPS, specifically in relation to energy aspects, throughout the entire building life cycle. It discusses the current level of abstraction in building modeling and its limitations, and proposes potential levels of building energy models based on sensitivity analysis and the building design process.

3.2 Related Work

Sensitivity analysis has been widely used in Building Energy Modeling (BEM) to assess the impact of different parameters or variables on the performance of the model. It enables the identification of key parameters in a model that have a significant impact on the defined outcome, and helps in understanding their relative importance and interactions. This allows designers to focus on the most important parameters when making design decisions, and prioritize design strategies accordingly. Tian provides an in-depth review of sensitivity analysis methods for building energy models [200].

For example, Heiselberg et al. [99] found that lighting control and the amount of ventilation contribute the most to a building's total energy consumption. However, they also noted that if the analysis is not based on total energy consumption, but rather separately on heating or cooling demand, the ranking of parameters changes significantly. Delgarm et al. [59] explored the effect of a simulated multi-story building in the different climate zones of Iran, including warm-dry, warm-humid, and cold climates. They found that window size was the most influential variable for total building energy assessment. Gagnon et al. [83] applied sensitivity analysis at different stages of the design process to understand the outcome of fixing variables throughout the design stages. In their studies, they evaluated 30 design variables that affect energy consumption and thermal comfort of a real-world 5-story office building, and found that parameters such as relative humidity set point, window-to-wall ratio, and solar heat gain coefficient were among the most significant factors. Eisenhower et al. [70] generated a meta-model using EnergyPlus of an existing mixed office-gym building to analyze over 1000 parameters to optimize building energy. Among analyzing these parameters, they found that schedules for load, outdoor air fraction, and supply air temperature set point have a substantial impact on comfort and energy consumption in a building.

Despite several studies that have been carried out in sensitivity analysis of building energy models, few have focused on the fact that the importance of parameters changes based on building typology and location. Furthermore, most studies examine energy simulations as a whole and do not apply them to different design stages to assist in informed design decision-making. Although Gagnon et al. [83] apply sensitivity analysis at various design stages, they only studied one building in one climate zone. Our study focuses on sensitivity analysis of small office buildings at different design stages across all climate zones in the United States. We aim to provide insights on how different abstraction models throughout the design process can assist designers in making informed decisions.

Existing Data Standards

BIM is a digital representation of the physical characteristics of a building, encompassing information such as building geometry, materials, spatial relationships, and electrical components. BIM models are typically created and managed using specialized software such as Autodesk Revit [20], GraphiSoft Archicad [92], Bentley OpenBuildings Designer (formerly AECOsim) [28], and Siemens Ecodomus [167]. These BIM software tools allow for the creation, visualization, and analysis of detailed building models, and support collaborative workflows among stakeholders. BIM software typically supports importing and exporting of data in one or more standard data formats, allowing for interoperability and exchange of information among different software tools.

The standard non-proprietary data exchange formats commonly used for BIM are the IFC [107] and gbXML [86]. IFC stores building data, including geometry, spatial elements, and sensor information, and allows for the exchange of comprehensive and rich data related to building components, systems, and properties. IFC supports various shapes and geometries, allowing for detailed and complex building representations. Construction Operation Building Information Exchange (COBie) [67], a subset of IFC, is a performance-based specification that includes equipment and spaces. It is commonly used for data exchange related to facility management, operation, and maintenance. gbXML, on the other hand, is a format specifically used in the energy simulation domain. It facilitates the exchange of data between CAD and energy analysis tools, allowing for the transfer of building geometry, materials, and other relevant data for energy performance analysis. However, gbXML only supports rectangular shapes for building geometry or objects, whereas IFC can record any shape, making IFC more versatile for complex building representations. The data structures of the IFC and gbXML are shown in Figure 3.1.

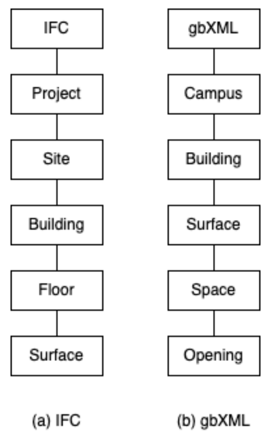

Figure 3.1: Data structures for the IFC and gbXML format.

Although the communication between BIM and BPS is established, it is not yet fully developed. The process of transferring data between these tools may not be fully automatic and may require manual alterations when applied to different software platforms. For instance, in BIM software like Revit, the thickness of a building element can be defined for each material. However, when transferring the model to an energy simulation tool like EnergyPlus, a new material input may be required for each defined thickness, which can be cumbersome and time-consuming [41]. This limitation in interoperability between BIM and BPS tools highlights the need for further advancements in data exchange standards and processes.

Level of Detail of BIM

While the level of abstraction for BEM may not be well-defined, the concept of the Level of Detail (LoD) framework in BIM has been developed by the American Institute of Architects (AIA) [14] as shown in Table 2.1 in the previous section. LoD defines the amount and degree of building information that needs to be included in the BIM at different stages of the project.

The LoD framework, originally developed for construction purposes, is not directly applicable to energy models. For example, BPS tools separate spaces into different thermal zones rather than rooms and floor plans. In addition, estimated occupancy schedules, which are important factors affecting energy performance, are not included as part of the model description [104]. Despite these limitations, the differences between construction and energy analysis purposes can be managed within the same framework.

3.3 The Role of BPS Tools in the Building Design Process

In this section, we examine the significance of BPS tools at various stages of the building design process, including concept, schematic design, design development, construction, and operations, as illustrated in Table 3.1 [153].

Concept

This stage encompasses the preparation and evaluation stages of the integrative design process. Its main objective is to benchmark energy performance against similar buildings in the same area, and assess overall energy strategies based on climate data, requirements, and building end-use. A simplified energy massing model is typically used at this stage to explore passive energy-saving strategies, such as configuration and orientation options. Commonly used BPS tools for the early design stage include ENERGY STAR Target Finder [175], Sefaira [161], and cove.tool [183].

Schematic Design

During the schematic design stage, the overall energy performance goals of the building are refined into subsystems' energy performance goals, such as cooling, heating, lighting, and plug-load systems. Additionally, an appropriate baseline of energy performance is determined for comparison. The model can inform design choices related to thermal envelope parameters and load reduction strategies, with the aim of reducing load and cost while maintaining indoor environmental quality.

Design Development

The building geometry is firmly established by this stage. Iterative parametric modeling is performed to explore the options in Mechanical, Electrical, and Plumbing (MEP) systems. Designers can make informed decisions based on simulation outcomes, allowing for optimization of MEP system designs to achieve desired energy performance targets.

Construction

By the end of the design development stage, the building model is fully established. However, during the construction phase, variations in materials, geometry, and other factors may

Table 3.1: The role of BPS tools in the building design process.

	Concept	**Schematic Design**	**Design Development**	**Construction**	**Operation**
BPS Goals	• Initial evaluation of overall energy strategies based on climate data and building purposes • Benchmark energy performance of similar buildings • Establish overall energy performance target • Simple energy model to explore configuration and orientation options	• Refine energy performance goals and add in subsystems' energy performance goals • Determine an appropriate baseline for comparison • Develop strategies for load reduction	• Analyze the interaction between all systems and their impact on energy performance • Perform iterative parametric modeling on the impacts of mechanical, electrical, and plumbing design • Representative load calculations • Fine-tuning the details through optimization	• Monitor construction process and update model parameters as appropriate	• Identify the performance gap between the model and the actual building • Real-time data collection from the actual building • Optimize operations for further energy reduction
BPS Tools	ENERGY STAR Target Finder, Sefaira, cove.tool	eQUEST, VisualDOE, HAP, TRACE, IES-VE, Design Builder, EnergyPlus, TRNSYS, Modelica			

deviate from the design phase. Therefore, continuous monitoring and updating of the model are necessary to facilitate informed decisions, if needed, during construction to ensure that the as-built building aligns with the intended energy performance goals.

Operation

After the building is constructed and occupied, real-time data can be collected from the actual building to calibrate the energy model. This allows for addressing and identifying any potential performance gaps between the model and the actual building. Furthermore, optimizing the building's operation while maintaining occupant comfort can lead to further energy reduction. Moreover, the energy model can be utilized for various applications, such as fault detection and grid response, enhancing its usefulness beyond just design and construction stages.

Gaps

There are energy performance tools at early design stages to estimate energy consumption based on similar buildings in the same climate zone. However, throughout the design stages, there are still gaps that need to be addressed to improve the accuracy and usability of BEM tools. One of the gaps in existing BEM tools is the absence of partial BEM tools that allow for estimation of energy performance without the need to build a full model. Currently, designers are required to create a complete BEM model, which can be time-consuming and resource-intensive, even during early design stages when only rough estimates are needed. This creates unnecessary complexity and can hinder the design process. Another challenge is the uncertainty of parameters in BEM tools. Many input parameters, such as occupancy patterns, weather data, and equipment efficiencies, are subject to uncertainty. However, existing BEM tools often do not adequately account for the uncertainty of these parameters, which can lead to overly optimistic or pessimistic energy performance estimates. Uncertainty analysis is crucial in evaluating the overall energy performance of a building and providing designers with holistic information for decision-making. Therefore, incorporating robust methods to account for uncertainty in BEM tools is a necessary improvement. Furthermore, the lack of clear guidance on model selection throughout the design stages is another limitation. Designers often struggle to determine which BEM tool or approach is most appropriate for their specific needs at different stages of design development. This can lead to inconsistencies and inaccuracies in energy performance estimation, impacting the final building's performance.

In the following sections, we aim to address the gaps in developing partial building energy models and reducing uncertainty to better support designers in creating energy-efficient buildings.

3.4 Methodology

Building Models

We utilized prototype building models developed by the Department of Energy (DOE)[2]. These models are created in EnergyPlus [57], a widely used BEM tool, and encompass a diverse range of building types, including both commercial and residential buildings, across eight different climate zones in the United States. Specifically, our analysis focused on *small office buildings* in all eight climate zones, which include hot-humid, hot-dry, mixed-humid, mixed-dry, cold, very cold, subarctic, and marine regions as depicted in Figure 3.2 (Note that the subarctic region (Alaska) is not shown in the Figure). These prototype building models provide a standardized and representative basis for evaluating the energy performance of small office buildings in various climatic conditions, allowing for consistent and comparable analyses across different regions.

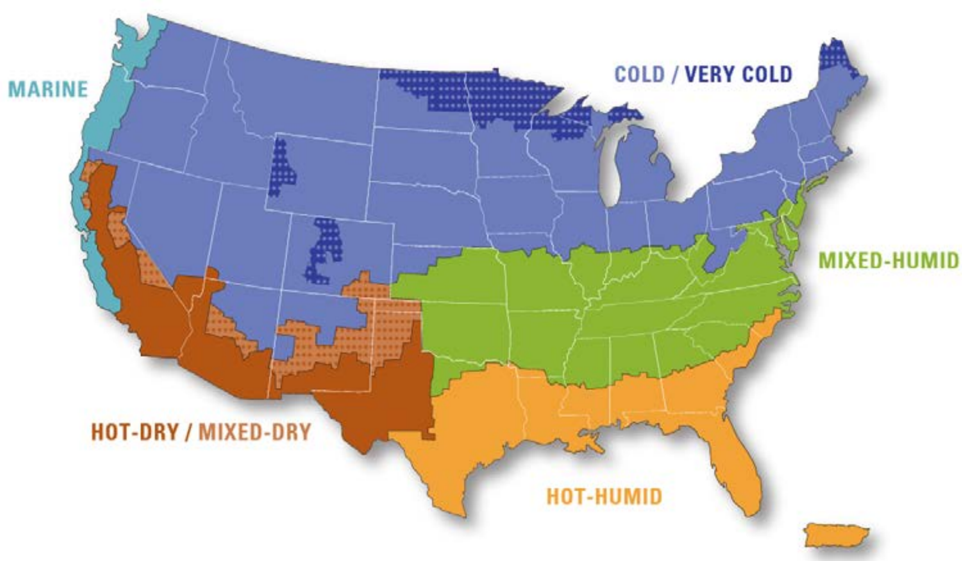

Figure 3.2: United States Climate Zone Map. Note: the subarctic zone (Alaska) is not shown on the map [122].

The small office building consists of one central room with four rooms adjacent to its side as shown in Figure 3.3. To gain insights into energy consumption and identify critical parameters, sensitivity analysis is conducted throughout the design stages, as parameters are decided during the process. This analysis is performed across all climate zones, allowing designers to understand the impact of different parameters on energy performance in various environmental conditions.

[2]https://www.energycodes.gov/prototype-building-models

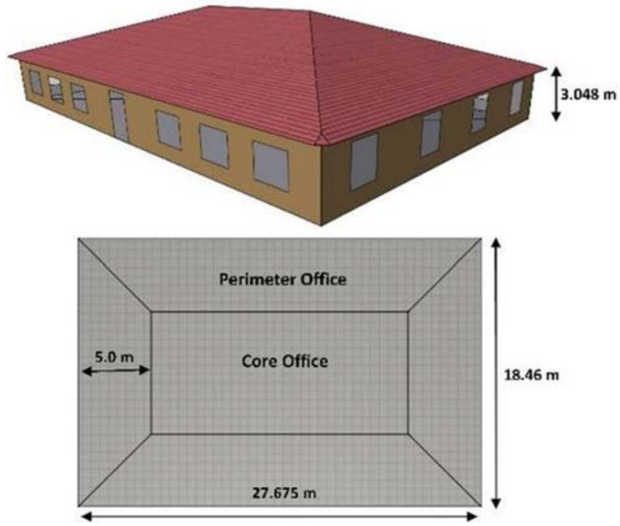

Figure 3.3: Small office building

Sensitivity Analysis Method

The Morris method [141], implemented in Python using SALib library [101], is used for performing sensitivity analysis. It is a type of global sensitivity analysis that follows a one-factor-at-a-time (OAT) approach. In this approach, random perturbations are applied to one input parameter at a time to create trajectories. The model output is then evaluated for each trajectory, and the sensitivity value is calculated based on the magnitude of changes in the model output. One of the major advantages of the Morris method is its computational efficiency, making it suitable for running sensitivity analyses with a large number of parameters. This method can provide useful insights into the impact of each parameter on the model output, indicating whether a parameter has minimal impact, behaves in a linear and additive manner, or exhibits non-linear effects or interactions with other input parameters.

The Morris method employs statistical measures such as average and standard deviation to quantify the sensitivity of each input parameter. The average sensitivity measure, denoted as μ^* is calculated as follows:

$$\mu^* = \frac{1}{N}\sum_{i=i}^{N}\frac{|y_i' - y_i|}{\Delta} \tag{3.1}$$

where N is the number of trajectories, y_i' is the model output for the perturbed input parameter, y_i is the model output for the unperturbed input parameter, and Δ is the perturbation size. The standard deviation sensitivity measure, denoted as σ, is calculated as follows:

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\frac{|y_i' - y_i|}{\Delta} - \mu^*)^2} \tag{3.2}$$

By examining the relationship between μ^* and σ, the Morris method can provide valuable insights into the relative importance and interactions between input parameters. If μ^* is high and σ is low, this indicates that the parameter has a significant linear effect on the model output. If both μ^* and σ are high, this indicates that the parameter has a significant non-linear effect on the model output. Changes in this input parameter result in unpredictable and non-linear changes in the model output. If both μ^* and σ are low, this suggests that the input parameter has minimal impact on the model output and there is no interaction with other parameters. Finally, if μ^* is low and σ is high, this suggests that the input parameter may be interacting with other parameters in a non-linear way, leading to unpredictable changes in the model output.

Approach

We conducted a sensitivity analysis on small office building EnergyPlus models in eight distinct climate zones within the United States. We aim to investigate how climate conditions influence the relative importance of various parameters in whole building energy models. Next, we divided the parameters into five stages based on the typical design process, with further details provided in the Results section. At each stage, we fixed the design variables and performed sensitivity analysis on the remaining parameters to understand their impact on the model outcomes. Our approach builds upon similar studies conducted by Gagnon et al. in [83], but expands the concept by considering various climate zones in the United States. Additionally, we investigate how the results of our sensitivity analysis can be utilized for design optimization of these parameters, and provide insights into the levels of abstraction in building energy models.

Input Parameters

The selection of parameters for sensitivity analysis is crucial as it directly impacts the outcomes and reliability of the analysis. Here, we describe how the parameters are chosen and how the range is decided. In this study, we carefully chose parameters based on previous research findings that demonstrated their significant impact on building energy outcomes, including building envelope properties, loads, window properties, HVAC efficiency, and temperature set points [59, 70, 83, 99]. These parameters will be the main focus of our sensitivity analysis. The schedule of operations, such as working hours and occupancy patterns, was not included as a parameter in this study. This decision was mainly due to the typically fixed schedule of office spaces and the challenges associated with changing working hours in real-world office buildings. However, we acknowledge that the schedule of operations can also impact building energy performance, and its exclusion from our sensitivity analysis may introduce limitations in our analysis.

The orientation of the building is set between 0 and 90 degrees due to the building's symmetry. The window properties, including U-factor (u_w), Solar Heat Gain Coefficient (SHGC), and Window-to-Wall Ratio (WWR), are also important factors. According to

ASHRAE 90.1 [69], typical ranges for u_w are 0.2 to 1.2, and for SHGC, 0.1 to 0.45. It's worth noting that material cost is not considered in this analysis. For instance, a U-factor of 0.2 is considered expensive, while a U-factor of 1.2 is considered subpar. SHGC is a parameter that describes the amount of solar heat that can pass through a window, with lower values indicating less heat transfer. Sayadi et al. [159] and Goia et al. [91] found that the ideal WWR is between 30% to 50%, but in different climate zones, the typical WWR can range from 20% to 70%. Insulation layers, including the resistance of the roof and exterior walls, are other important properties in determining the energy consumption of a building. The resistance range is calculated based on the R-values in ASHRAE 90.1 [69]. The infiltration rate, which specifically relates to exterior door openings, is set between 0.6 and 4.5 m^3/s based on recommendations from Cho et al. [51]. Parameters related to HVAC systems are also considered. The Coefficient of Performance (COP) is used as a measure of efficiency for cooling and heating systems, with typical ranges of 1 to 3.4 for cooling and 1 to 4 for heating [152]. The heating and cooling set points for indoor air temperature are recommended by ASHRAE 55-2010 [17], and the heating and cooling supply air temperature ranges are based on recommendations from Gagnon et al. [83]. The fan efficiency ranges are defined by TRANE [185]. Finally, loads of lighting, electric equipment, and occupancy are estimated based on data from ASHRAE 2021 Handbook [154].

Table 3.2: Input parameters list for sensitivity analysis.

Index	**Symbol**	**Description**	**Range**	**Reference**
0	u_w	U-factor of window [W/m^2K]	[0.2, 1.2]	[69]
1	SHGC	Solar heat gain coefficient of window [-]	[0.1, 0.45]	[69]
2	θ	Orientation of the building [°]	[0, 90]	
3-6	WWR	Window-to-wall ratio of each wall facet [%]	[20, 70]	[91, 159]
7	R_{ins}	Thermal resistance of the exterior wall insulation layer [m^2K/W]	[0.3, 6]	[69]
8	R_{roof}	Thermal resistance of the roof insulation layer [m^2K/W]	[0.6164, 10]	[69]
9	Q_{inf}	Exterior door infiltration rate [m^3/s]	[0.6, 4.5]	[51]
10	COP_c	Gross rated cooling coefficient of performance [W/W]	[1, 3.4]	[152]
11	COP_h	Gross rated heating coefficient of performance [W/W]	[1, 4]	[152]
12	η_{fan}	Fan total efficiency [-]	[0.4, 0.9]	[185]
13	$\eta_{m,\text{fan}}$	Fan motor efficiency [-]	[0.6, 0.9]	[185]
14	A	Zone floor area per person [m^2/person]	[7.9, 15.5]	[154]
15	LPD	Lighting power densities [W/m^2]	[6.6, 8.0]	[154]
16	P_{elec}	Electric equipment loads [W/m^2]	[3.67, 12.3]	[154]
17	$T_{\text{sup, c}}$	Cooling design supply air temperature [$°C$]	[12, 18]	[83]
18	$T_{\text{sup, h}}$	Heating design supply air temperature [$°C$]	[30, 40]	[83]
19	$T_{\text{set, c}}$	Cooling set point air temperature [$°C$]	[25, 27]	[17]
20	$T_{\text{set, h}}$	Heating set point air temperature [$°C$]	[19, 23]	[17]

3.5 Results

Sensitivity Analysis across All Parameters

Figure 3.4 illustrates the outcomes of sensitivity analysis conducted across eight distinct climate zones. The findings indicate that for hot-dry and hot-humid climates, the key parameters with substantial impact on energy consumption are cooling effectiveness (COP_c), equipment loads (P_{elec}), and Solar Heat Gain Coefficient (SHGC). In hotter climates, solar radiation is an important factor that affects energy consumption, making SHGC an important parameter for blocking heat transmission to indoor space. Moreover, cooling effectiveness becomes crucial in ensuring efficient cooling operations in such climates. In addition to SHGC and COP_c, equipment loads (P_{elec}) also plays a crucial role in hotter climates. As equipment emits heat during operation, proper management of heat produced by the equipment is important to reduce energy consumption. In mixed-dry and mix-humid climates, the most influential parameters are P_{elec} and R_{roof}. Lastly, in colder climates such as marine, cold, very cold, and subarctic, the building envelope parameters, including roof insulation (R_{roof}), exterior wall insulation (R_{ext}), and infiltration rate (Q_{inf}), have the most notable impact on energy consumption. This is because, in colder climates, better insulation of the building envelope can help prevent heat from escaping and reduce the need for excessive heating, resulting in lower energy consumption and improved energy efficiency.

Figure 3.5 illustrates the distribution of yearly energy consumption across various parameters, as outlined in Table 3.2, for all eight different climates. In the majority of climates, the energy consumption falls within the range of 100 to 400 $kWhr/m^2/annum$. However, in colder climates, the energy consumption tends to be higher, ranging up to 700 $kWhr/m^2/annum$. This observation underscores the significance of considering energy consumption during the initial stages of design, particularly in colder climates where energy demands tend to be higher.

Sensitivity Analysis throughout the Design Stages

In the previous section, we utilized sensitivity analysis to identify the most influential variables with respect to energy consumption in building models. In this section, we have further divided the design parameters to align with the different stages of building design, following the typical order in which designers make decisions. We have categorized them into five decision sets, labeled as S0 to S4, as depicted in Figure 3.6. During each decision-making stage, certain parameters are determined, while others remain undecided. These undecided parameters will undergo additional sensitivity analysis to assess how the decisions made on some parameters impact the remaining parameters and ultimately affect the energy outcomes of the building. We begin with all 21 variables, as listed in Table 3.2.

In decision set S1, which occurs after the concept stage, the building orientation is typically determined. Additionally, based on the building type, estimations of load, lighting, occupancy, and infiltration can be established. Moving on to the schematic design stage, in

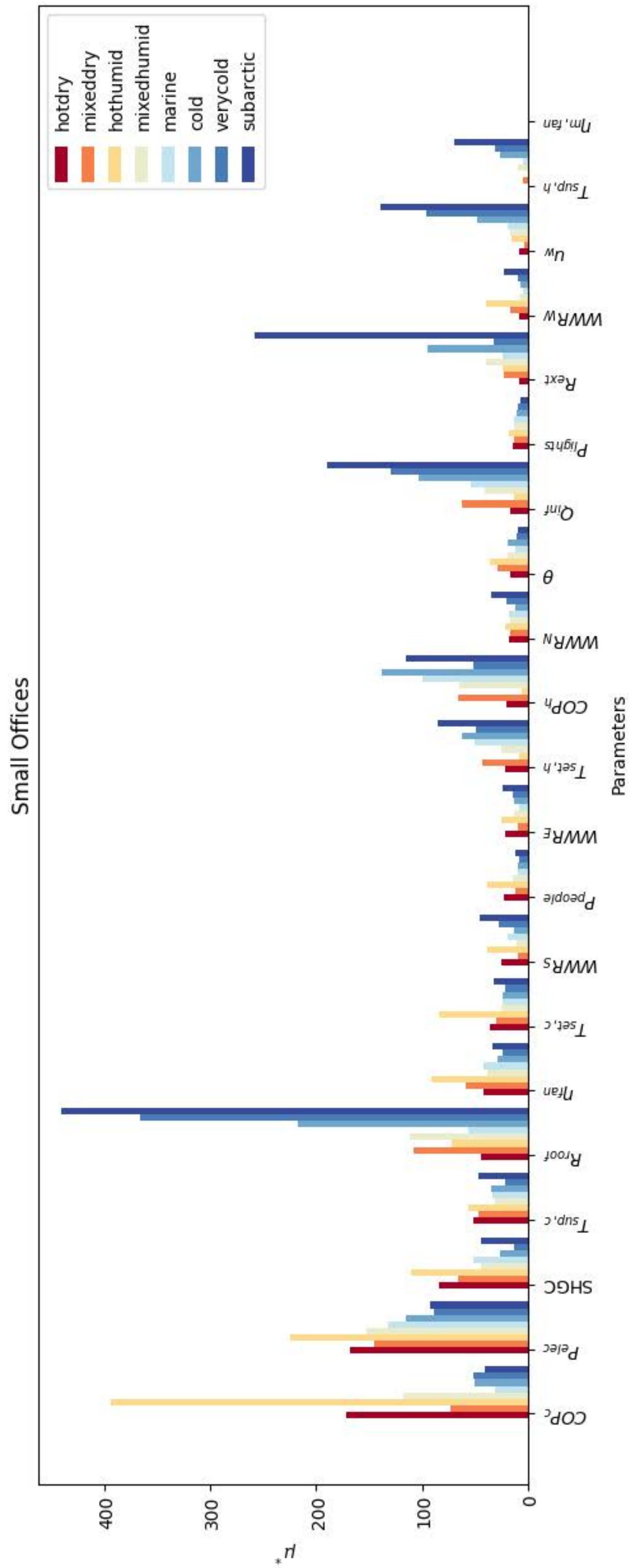

Figure 3.4: Sensitivity analysis of all parameters across eight different climate zones.

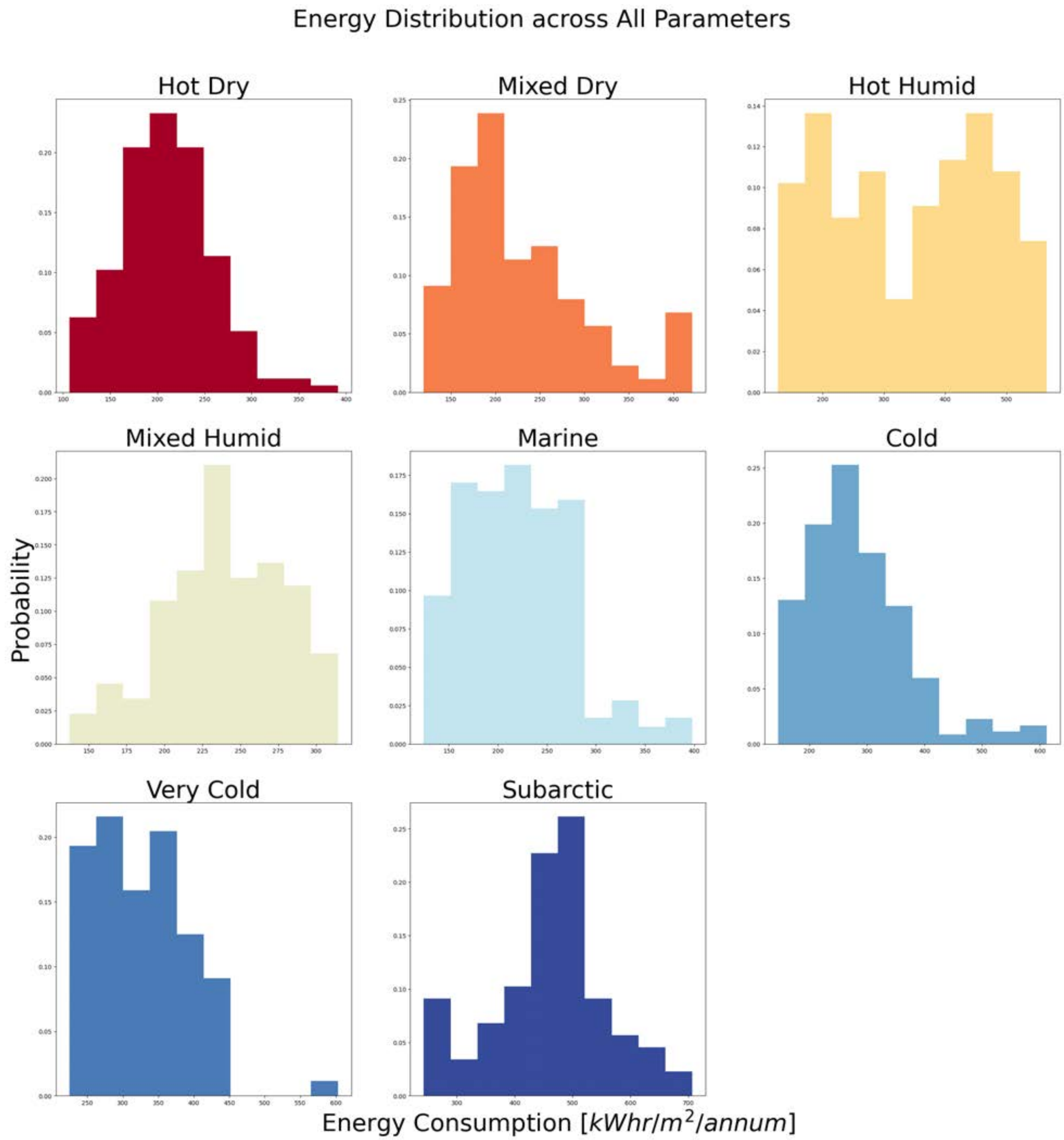

Figure 3.5: Energy distribution for eight different climate zones, including hot-dry, mixed-dry, hot-humid, mix-humid, marine, cold, very cold, and subarctic climate zones.

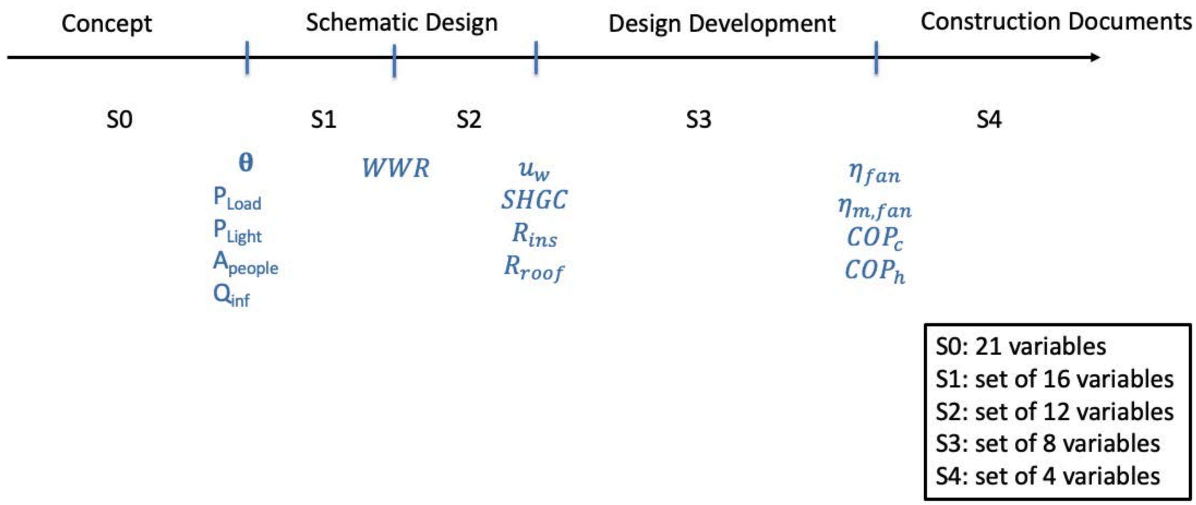

Figure 3.6: Parameters decisions throughout the design stages.

decision set S2, the WWRs for all four facing walls are determined. Furthermore, in decision set S3, building envelope parameters such as U-factor (u_w) and SHGC of windows, as well as resistance values of roof materials and exterior wall materials, are decided. Finally, in decision set S4, HVAC parameters are defined, including the efficiency of fans (η_{fan} and $\eta_{m,fan}$) and the COP of coolers and heaters.

For illustrative purposes, we apply sensitivity analysis throughout different stages of design in a hot-dry climate. The results of sensitivity analysis are presented in Figure 3.7. We also examined the energy distribution at each decision set, as shown in Figure 3.8. In decision set S1, we found that only one influential parameter, P_{elec}, had a significant impact on the total energy consumption of the building, while the other parameters had less influence. While P_{elec} is an estimation based on the building type, it emphasizes the importance of accurately estimating this parameter in order to obtain an accurate prediction of energy consumption. In decision set S2 and S3, the selected variables did not contribute significantly to the energy outcomes of the building. As shown in Figure 3.8, the range of energy outcomes did not change significantly. However, in decision set S4, which involves the most important design parameters, the decisions made had a significant impact on overall energy consumption. It's also important to note that after fixing some variables at each stage, the significance of parameters may change slightly due to the interdependencies among variables and the context of the specific design scenario. This highlights the dynamic nature of the design process and the need for continuous evaluation and refinement throughout different stages of design.

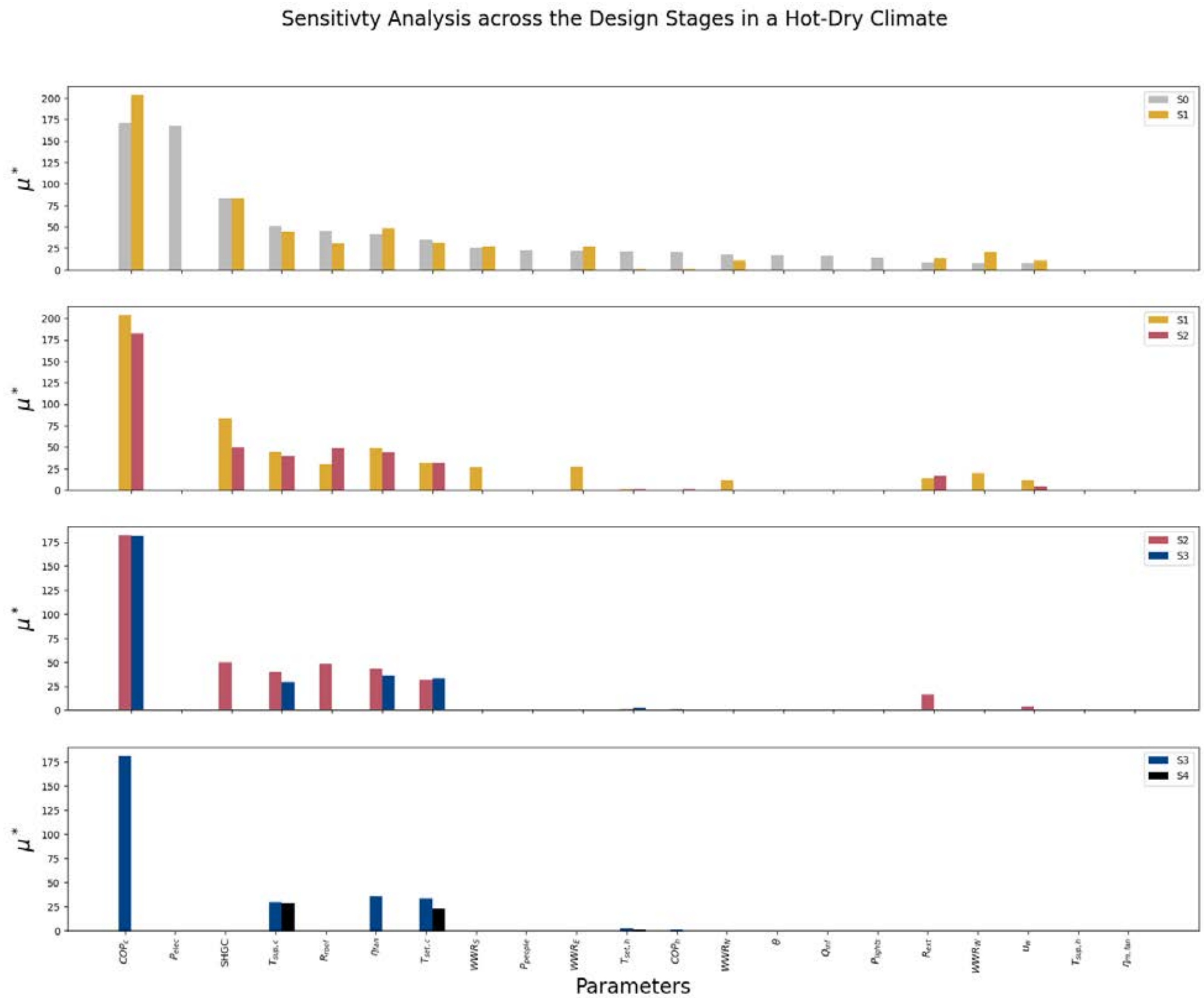

Figure 3.7: u^* of each variable at different design-decision stages for a small office building in a hot-dry climate zone.

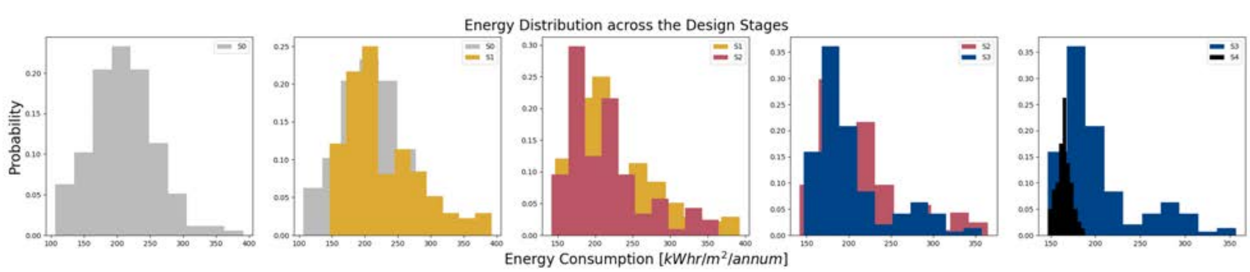

Figure 3.8: Energy distribution at each design stage.

Sequential Design Optimization

Building design is a complex and iterative process that involves making decisions sequentially, taking into consideration the outcomes of previous decisions. The decisions made at earlier stages of the design process can have a significant impact on the decisions made at later stages, and the overall performance of the building. Our goal is to provide a comprehensive understanding of the energy outcomes associated with each decision made at different stages of the design process.

To achieve this, we assign parameters at different levels of abstraction throughout the design process. This allows researchers to create models that can support decision-making at each level without the need for a full building model. As shown in Figure 3.9, each decision set corresponds to a model that provides information on how energy distribution changes based on the decisions made regarding the parameters.

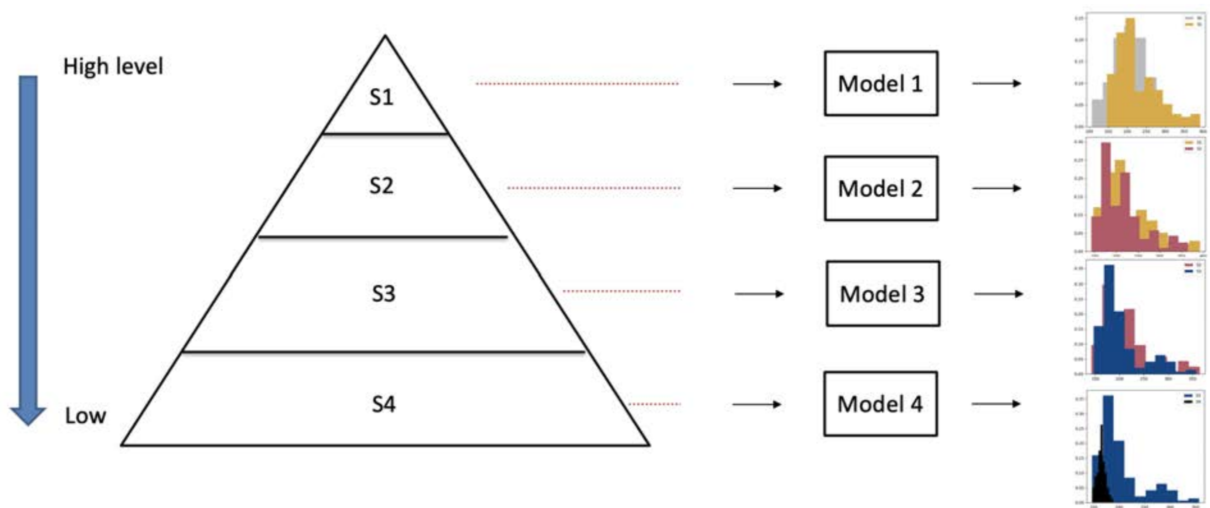

Figure 3.9: Levels of abstraction for building energy models.

Data-driven methods and causal inference techniques have shown promising potential in developing such models, enabling us to capture the complex interactions and dependencies among various design parameters and their impact on energy outcomes [45, 46]. While we currently perform exhaustive searches on a whole building energy model to meet energy objectives, in the future, sequential design optimization techniques can be applied once each model stage is well-defined. This would enable us to optimize the design decisions in a sequential manner, taking into account the outcomes of previous decisions, and iteratively refining the design to achieve optimal energy performance.

3.6 Chapter Summary

Building design involves a multi-stage process that requires decisions to be made at different design stages. These decisions impact the overall performance of the building, and optimizing them can lead to more energy-efficient and sustainable designs. However, currently, there is no clear definition of levels of abstraction for each design stage, which results in disorganized building energy models throughout the design process. In this chapter, we attempt to apply sensitivity analysis at different stages of the design process to understand the sensitivity of building performance to various design decisions and help create different levels of abstraction for building models. The results of sensitivity analysis can guide decision-making by prioritizing the most important parameters and focusing resources on optimizing their values.

However, it's important to note that even for the same building type, the significant parameters can differ based on the climate zones, making it difficult to provide a standardized approach. Nonetheless, the decision-making process in building design should align with one another to some extent, and building energy models can be the first step to realizing levels of abstraction in order to better support decision-making. This can streamline the modeling process and provide probabilistic estimates of expected energy consumption at each stage, showing how decisions on various parameters can impact energy performance.

While this study provides valuable insights into the sensitivity of building design decisions to selected parameters, it is important to note that not all parameters were evaluated. Building form and shading, for example, can have a significant impact on building performance, and their inclusion in future studies could provide a more comprehensive understanding of the sensitivity of building design decisions. Moreover, it is important to acknowledge that the Morris method used in this study is limited to linear relationships and does not capture interactions between parameters. To gain a better understanding of parameter interactions, it may be necessary to explore other sensitivity analysis techniques, such as the Sobol method, that can account for nonlinear relationships and interactions between parameters. Furthermore, it is important to analyze different building typologies to fully understand how building designs respond to parameter changes, as the type of building can also significantly affect its performance. Each building type may require a unique focus on different parameters to optimize its design, and an analysis of these requirements could inform more effective design decision-making. Future research could also focus on developing decision support tools that integrate different levels of abstraction into the design process, providing designers with real-time feedback and recommendations for optimizing design decisions. This could help bridge the gap between the theoretical concept of levels of abstraction and their practical application in building design decision-making. Lastly, building energy models can also be further improved to incorporate other building performance factors, such as comfort and indoor air quality, to provide better trades-off among multiple objectives.

Chapter 4

Synthesis of Building Models[1]

4.1 Background

In the previous chapter, we analyzed building models throughout the design stages. In this chapter, our focus shifts to synthesizing building models for existing buildings by incorporating data from real-time sensors, commonly known as Digital Twins (DTs).

The term DT emerged in 2012, where it was defined as a virtual space that fully describes the corresponding physical system [93]. In other words, a DT allows us to obtain information from the physical space through its virtual counterpart, and the data between the two remains in sync, ensuring real-time accuracy. The concept of *twin* systems originated from NASA, where a *physical* twin was maintained on the ground to assist in troubleshooting issues that may arise in space [160]. Subsequently, it was first implemented in GE Research [148] for jet engines, where sensors connected information between physical and virtual systems to monitor system faults and maintenance needs effectively. DT technology opens up significant opportunities for monitoring energy consumption in existing buildings and facilitating the transition to Net-Zero Energy Buildings (NZEBs). This advancement has the potential to revolutionize the way buildings are managed and maintained, leading to more sustainable and energy-efficient building practices.

DT applications lie broadly in product design, production, prognostics, and health management [181]. DT facilitates manufacturers by enabling them to make more accurate predictions and informed decisions, and reduce human errors by providing well-rounded information. Currently, most DT research has been focusing on smart manufacturing, where they use DT to improve product planning and fault detection. Tao et. al. studied data fusion techniques of a DT shop floor between the physical and virtual space [180]. Cai et. al. developed a DT of vertical milling machine by integrating manufacturing and sensor data [38].

Limited research studies have been made for DTs of the built environment. There are research studies that build DTs of energy management in a smart city where they monitor

[1]This chapter is a modified and extended version from references [128, 131].

smart meter electricity data of buildings [79]. However, besides electricity consumption, no other information is available for buildings in this study. In addition, most existing research discusses the framework of building a DT, but lacks empirical experiments on the topic.

There are three different modeling approaches commonly used for building DTs in the built environment: *white* box, *black* box, and *gray* box models. The white box model involves employing first-principle modeling techniques to capture the dynamics of the physical systems, taking into account their internal behavior and structure. In contrast, the black box model neglects the internal behavior of the system and focuses solely on data-driven approaches, often using machine learning algorithms to create a virtual representation based on observed data. The gray box model finds a balance between accuracy and complexity by incorporating both first-principles and data-driven approaches. Each modeling approach has its strengths and weaknesses, and the choice of modeling approach depends on the specific application, available data, and desired level of accuracy and complexity for the DT.

Table 4.1: Comparison between white box, black box, and gray box approaches.

	Advantages	**Disadvantages**
White Box	High fidelity High interpretability Extrapolation capacity	Difficult to Construct Computational expensive High uncertain parameters
Black Box	Easier to construct Less uncertain parameters	Low interpretability Risk over-fitting Limited extrapolation capacity
Gray Box	Can construct at the proper level of abstraction Reduce the number of uncertain parameters Moderate interpretability	Can be computational expensive Lack of a common platform

In the context of DTs, the white box approach, which involves building a virtual representation of the entire system in detail, is less commonly used. This is primarily due to the complexity of systems, which often require a multitude of parameters and make it challenging to achieve scalability or generalizability. However, there are some examples in the literature where physics-based models have been developed for specific applications. For instance, Aivaliotis et. al. developed a physics-based model of an industrial robot hand for predictive maintenance [8], while Prawiranto et. al. developed a physics-based DT to monitor solar drying processes [151]. Furthermore, there are several BPS tools that support energy consumption estimation of a building by capturing all the physical properties of the system and calculating the energy consumption based on heat balance equations. However, most of them are not specifically designed for DT purposes where parameters are in sync with the physical system, but rather for construction planning and energy consumption prediction. Additionally, they often require parameters that may not be readily available in the physical system, resulting in a large amount of uncertainty in parameter estimation.

On the other hand, several companies developed DT using a top-down approach that involves data integration and data fusion. Companies such as Johnson Control [55], Enertiv [190], and Willow [182] have developed DTs that incorporate spatial information, static information, and real-time sensor data for remote monitoring and fault detection purposes. Siemens has also developed DTs for power grids in Finland to improve data utilization and optimize operations [168]. Microsoft has created a platform, Azure Digital Twins, which supports modeling of various environments and enables connections to IoT devices, allowing for the integration of real-time data [174]. These approaches are often more scalable and adaptable to different systems compared to physics-based models, as they leverage data-driven techniques to capture system behavior in real-world scenarios.

While white box models have advantages in high fidelity, interpretability, and extrapolation capacity, building a physics-based model requires a deep understanding of a system's structures and operations and is therefore often difficult to construct. Additionally, when constructing a white box model, obtaining every required parameter from the physical system can be difficult. This increases the number of uncertainty parameters and can be computationally expensive to solve the systems of equations. In juxtaposition with white box models, black box models are easier to construct and can be created based on available sensor data. However, black box models are rarely physically interpretable, may suffer from over-fitting, and have limited extrapolation capacity. In contrast, gray box models find a middle ground between white box and black box models, leveraging available sensor data while also incorporating some level of physics-based understanding. Table 4.1 summarizes the advantages and disadvantages of the three different approaches.

Despite the availability of various modeling techniques for building systems, there is a notable gap in comprehensive performance indicators for these models, leading to uncertainty when it comes to selecting the most suitable model for a particular application. Most studies tend to focus solely on accuracy as the primary performance metric, without considering other important attributes of model performance.

In this chapter, we compare three different types of models in terms of multiple performance criteria. These criteria include accuracy, execution time, measurement cost, prediction horizon, and output resolution. By considering these diverse aspects of model performance, we aim to provide a more holistic and comprehensive evaluation of the different modeling techniques used in the field of building systems. Furthermore, we present a platform-based design framework for constructing building models. This framework provides a structured approach to model building at an appropriate level of abstraction for a specific application.

4.2 Modeling Types

In the context of buildings, white box, black box, and gray box models are further elaborated below.

"White Box" Modeling

The white box model involves employing first-principle modeling techniques to capture the dynamics of the physical systems in detail. It is based on fundamental laws of physics and engineering principles and typically requires a deep understanding of the system's internal behavior and structure. The main mathematical equations that are used in building modeling include heat transfer equations, energy conservation equations, mass flow equations, and control equations [154].

In building modeling, an accurate representation of heat transfer processes is essential for predicting the thermal behavior of buildings under different conditions, such as varying outdoor temperatures, solar radiation, and internal loads. Heat transfer equations, such as conduction, convection, and radiation, are used to model the heat flow through walls, roofs, windows, and other building components. Conduction heat is the transfer of thermal energy through a solid, the equation is shown as follows:

$$q_{con} = k\frac{(T_{s_1} - T_{s_2})A}{L} \tag{4.1}$$

where k is thermal conductivity (W/mK), T_{s_1} and T_{s_2} are temperatures of the contacted surfaces, L is the thickness (m), and A is the contact area (m^2). Convective heat transfer is the transfer of thermal energy between a surface and a fluid, equation is shown as follows:

$$q_{cov} = h_c A(T_s - T_a) \tag{4.2}$$

where h_c is the convective heat transfer coefficient (W/m^2K), A is the heat transfer area of the surface (m^2), T_s is the temperature of a surface ($^\circ C$), and T_a is the temperature of a fluid ($^\circ C$). Lastly, radiation is the transfer of heat energy from one object to another through electromagnetic waves, without the need for any intervening medium. Its equation is shown as follows:

$$q_r = h_r A_s(T_s - T_{surr}) \tag{4.3}$$

where h_r is the radiation heat transfer coefficient that equals to $\sigma\eta(T_s^2 + T_{surr}^2)(T_s + T_{surr})$, A_s is the surface area, T_s and T_{surr} are the temperatures of the surface and its surroundings.

The energy conservation equation states that energy cannot be created nor destroyed but only transferred or converted from one to another. It is used to balance energy flows in and out of a building, accounting for various energy sources, sinks, and losses.

The mass flow rate equation is based on the fundamental principle of the conservation of mass, which states that mass cannot be created or destroyed, only transferred from one location to another. This equation is particularly useful in predicting the movement and distribution of air and water within a building, as it provides an accurate means of calculating the amount of mass that is moving through a given area over a specified period of time. The mass flow rate is calculated by:

$$\dot{m} = \int \rho v dA = \text{constant} \tag{4.4}$$

where $\dot{m}$ is the mass flow rate (kg/s) across an area, v is the fluid velocity normal to differential area dA, and ρ is the fluid density. The use of mass flow rate is to prevent the influence of density and temperature in the calculation.

Lastly, control equations used in building modeling are also essential for accurately representing building behavior, particularly in managing HVAC system actions. These control strategies can include set point adjustments, scheduling, occupancy-based controls, demand-based controls, weather-based controls, and other rules or algorithms that dictate how the building systems should operate to achieve performance objectives, such as maintaining occupant comfort and minimizing energy consumption. The commonly used control algorithms in building modeling include Proportional-Integral-Derivative (PID) [173] control, Model Predictive Control (MPC) [5], Deep Reinforcement Learning (DRL) control [109].

Although white box models can provide a comprehensive representation of the physical system, they can be complex, difficult to calibrate, and computationally demanding. EnergyPlus [57], TRNSYS [172], ESP-r [73], and Modelica [81] are popular simulation tools used for physics-based modeling in the field of building simulations.

“Black Box” Modeling

Black box models use data-driven methods to create a model based on observed data, without explicitly considering the underlying physical processes. With the advent of IoT technology, buildings are equipped with sensors that continuously collect measurements from various locations, reflecting real-time operations. This presents an opportunity to develop data-driven models for various building applications. For instance, building load prediction using black box models has emerged as a crucial aspect of improving building energy performance. Such predictions find applications in control optimization, fault diagnosis, and demand side management [213]. The most common methods used for building load prediction encompass various techniques such as regression, time-series forecasting, Artificial Neural Network (ANN), Support Vector Machine (SVM), and ensemble methods [162].

Black box models, while relatively simple to construct, have inherent limitations that need to be considered. One such limitation is their reliance on large amounts of data, which may be challenging to obtain or maintain in certain cases. Moreover, the accuracy and reliability of black box models are highly sensitive to the quality of the data used for training and validation, and their performance may deteriorate if the data quality is compromised. Another limitation is their fragility, as they may produce results that are not physically feasible, leading to unreliable outcomes. Black box models may also struggle in unseen or novel conditions, where their lack of adaptability and generalization capability may become evident. Additionally, black box models often lack interpretability, making it difficult to understand and explain their decision-making processes. Lastly, some black box models can be computationally expensive, requiring significant computational resources for training and inference. These limitations should be carefully considered when utilizing black box models in building modeling applications, and appropriate measures should be taken to mitigate these challenges.

“Gray Box” Modeling

Gray box models encompass various modeling approaches that fall between white box and black box models, and their definitions may vary depending on the context. Gray box models aim to preserve the relevant physical properties of the system while also incorporating data-driven techniques to capture system behavior. This allows for a more flexible and adaptive modeling approach that leverages both domain knowledge and available data for improved accuracy and predictive capability.

The Resistor-Capacitor (RC) thermal network is one of the most widely used modeling methods in the gray box approach because it provides a simplified representation of a building's thermal behavior and captures the essential dynamics of heat transfer and thermal storage in a computationally efficient manner. The model uses lumped parameters, such as resistance and capacitance, to represent thermal properties of the building elements, such as walls, roofs, and heaters, and their interactions with the indoor and outdoor environments. This simplification allows for efficient calculations of the building's thermal response over time, making it practical for real-time or near-real-time applications, such as building control [146, 171]. Although RC thermal networks have been widely used in building modeling, the design of an accurate thermal model is still challenging. The optimal selection of the number of resistors and capacitors for the model is not well-defined, and there is no clear consensus on the most appropriate configuration. Bacher et al. [21] conducted a study where they analyzed various model selections and found that the 3R3C model provided the best fit for a $120m^2$ building located in Denmark. However, it remains uncertain whether the same model configuration would accurately represent buildings of similar size and use in different locations or under different conditions.

The physics-based neural network is another modeling approach that falls under the category of gray box models. It combines the principles of physics-based modeling with the capabilities of neural networks. This hybrid approach aims to overcome some of the limitations of purely black box models by incorporating physical knowledge into the model structure. In a physics-based neural network, the architecture of the neural network is designed in such a way that it captures the underlying physics or fundamental principles of the system being modeled. This can be achieved by incorporating physical information through initialization [163], constraints [58], or model architecture [111]. By doing so, the model can learn from both data and prior knowledge of the system's physics, resulting in a more interpretable and physically meaningful model compared to fully black box models. However, there are limited studies that have explored the application of physics-based neural networks to the building modeling domain. One of the challenges is that they require a good understanding of the underlying physics and system behavior to design the appropriate neural network architecture and incorporate relevant physical constraints. Additionally, the availability and quality of data for training and validation can also impact the model's performance. Lastly, the computational cost of training and using neural networks can be higher compared to simpler modeling approaches.

Lastly, researchers also attempt to enhance physics-based models through data-driven techniques. First principle models often suffer from high levels of uncertainty. Data-driven methods can help compensate for these uncertainties and improve the overall prediction accuracy of the models. By incorporating data-driven approaches, such as machine learning or statistical methods, into physics-based models, researchers can leverage the power of data to calibrate and validate the models, resulting in more accurate predictions and a better understanding of the system behavior. For example, data-driven models are utilized in exploring the parameter space of physics models to calibrate and fine-tune them [124]. Additionally, some researchers employ data-driven models to construct reduced-order models by building black box surrogate models of partial systems, thereby reducing the complexity of a physics-based model [98, 112, 205]. Moreover, data-driven models can assist in speeding up the computational process of physics-based simulations [116]. By leveraging data-driven techniques in conjunction with physics-based models, researchers can enhance the accuracy, efficiency, and computational performance of building modeling approaches, leading to improved predictions, reduced computational costs, and an increased understanding of system behavior.

4.3 Creating a Digital Twin

Our goal is to establish a live connection between the physical and virtual space via sensor data in the built environment for the purpose of energy efficiency and occupants' comfort. Additionally, we seek to develop a performance metric system that can aid in determining the most suitable model to use for a specific application or purpose. We segment the development of DTs of the dynamic behavior of the HVAC system of a building into three distinct phases as shown in Figure 4.1. In phase I, we identify the components required to build the model of the physical systems. This involves identifying building elements and their interconnections. In phase II, we perform parameter identification and validation to match the model with the physical entity. This involves estimating the parameters of the model using available data from the physical system. The process of cycling between Phase I and Phase II may be repeated until the DT model can represent the physical system at a proper level of abstraction. Lastly, in phase III, we build the connection between the model and the physical systems for continuous monitoring and updates. The details for each phase are described.

Phase I: Model Construction

In the first phase, we identify the components that are required to create a complete system. To be university applicable to all building systems, we use the Brick schema [23] as data format to map the building components to models. Brick schema is a data schema that provides a hierarchical and extensible framework for describing the various components, systems, and properties of a building. An example data hierarchy is shown in Figure 4.2.

The Brick schema includes a rich set of classes and properties that allow for the representation of building elements, such as floors, rooms, zones, and HVAC systems, as well as

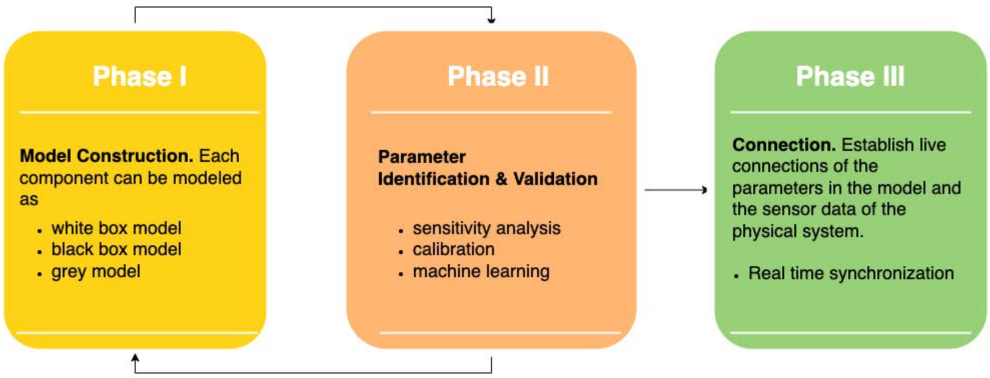

Figure 4.1: The three phases for developing a DT of a building.

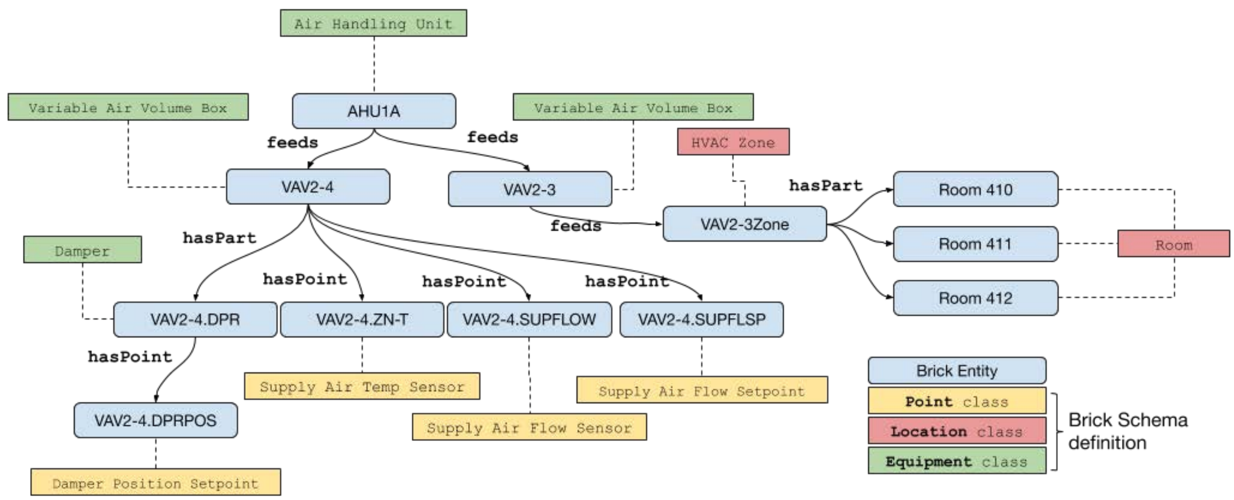

Figure 4.2: Brick Model Example [34]

the sensors and data points associated with these elements. It helps streamline the process of mapping sensor data to appropriate model parameters.

During the model construction process, our focus is on leveraging parameters that are directly available from the sensors in the physical system. However, we also acknowledge that there may be other parameters that are essential for accurate modeling but are not directly accessible without additional effort. To effectively model the physical system, we aim to break down the components into functional sub-blocks at an appropriate level of granularity. This allows us to represent each component as a *white box*, *black box*, or *gray box* based on the level of knowledge we have about its internal systems.

By categorizing the components into these different representations, we can effectively utilize the information we have from the physical system to create accurate and reliable models. This approach allows us to balance the trade-offs between model complexity and accuracy, taking into consideration the availability of information from the physical system during the model construction process.

Phase II: Model Identification

In the second phase, we identify and extract the parameters that are needed for the model from the physical systems. For black-box models, where we do not have knowledge of the internal system structure and only have access to the inputs and outputs of a particular component, we will employ machine learning techniques for function approximation. This involves using experimental data to train a machine learning model, such as a neural network with one or two hidden layers, to approximate the input-output relationship of the component. However, we need to be cautious about overfitting issues when fitting the data into the model to ensure its accuracy and reliability.

For gray box models, we will utilize both physics and machine learning techniques to estimate the values of the parameters. For instance, obtaining accurate physical properties, such as wall materials and resistance, of the walls in a room can be challenging. In such cases, we can create a gray box model using simple thermal circuit equations to estimate the envelope wall resistance of the room, leveraging the available information. To estimate the unknown parameters in the thermal circuit model, we can use techniques such as the unscented Kalman filter [192], which continually updates the mathematical model based on new measurements. This filter uses real-time measurements to correct the model's predictions, allowing us to refine the estimated parameter values and improve the accuracy of the model.

When dealing with complex models, especially white box models, there may be a large number of uncertain parameters that can influence the model's performance. To help identify which parameters are most critical, sensitivity analysis is often carried out. This involves varying the values of individual parameters while keeping all other parameters constant, to assess their impact on the model's output. We use the Morris method [141], a popular sensitivity analysis technique, implemented using the open-source Python Library, SALib [101]. This allows us to assess the sensitivity of the model to different parameters and prioritize calibration efforts accordingly. Once the uncertain parameters are identified, we perform calibration to match the model more closely with the physical space, ensuring its accuracy and reliability in representing the real-world system.

Phase III: Connecting a model to a phical building through Data

Lastly, we need to establish a connection between the physical entity and the model. The modeling parameters should be continuously updated with the gathered sensor data at an experimentally determined frequency. Figure 4.3 shows the data flow between the physical entity and the DT model. Ideally, when input values such as room set point temperature and supply air temperature are provided to both physical and virtual systems, the resulting

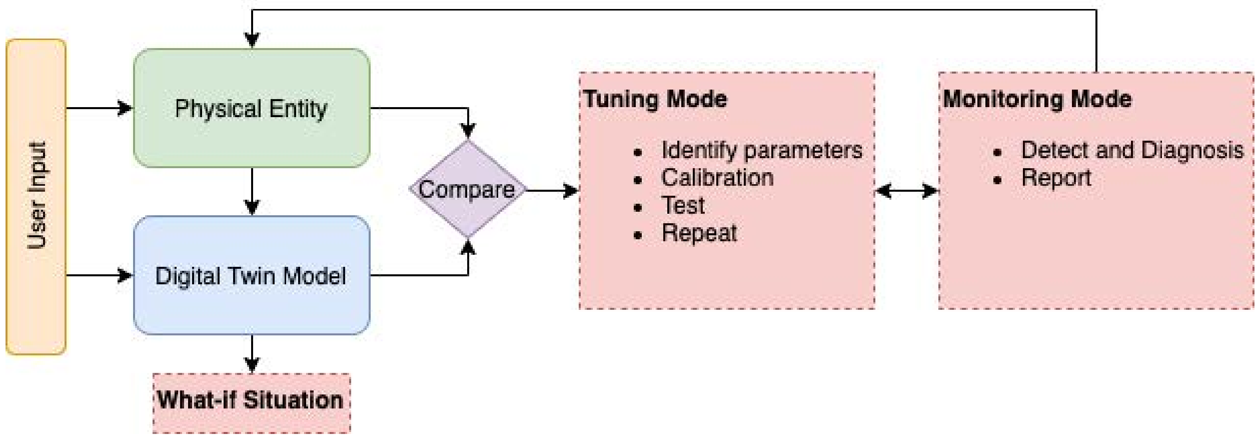

Figure 4.3: The block diagram showing the data stream between the physical entity and the digital twin model.

impacts on the overall system should be mirrored. The DT model will also receive additional inputs from the physical entity that are not the settings of the system, such as intermediate sensor data, occupancy, and equipment usage. The output values such as energy consumption will then be compared for further tuning or monitoring of the physical space. This ensures that the DT model continuously adapts to changes in the physical environment, minimizing model deviation. Moreover, DT can act as a platform for testing control algorithms and supporting decision-making in the physical system.

4.4 Experimental Example

Physical Testbed

Measurements are taken in a well-instrumented testbed located in Singapore. The indoor environment is shown in Figure 4.4. The testbed has the capability for high precision control and operations and the indoor environment is well-regulated. The size of the testbed is 25 m^2 with a height of $2.6m$. In contrast with a regular room in a building, the testbed is insulated from the outdoor weather. However, there exists an outdoor air emulator which emulates the outdoor environmental conditions.

There are more than 100 different kinds of sensors located in various places in the testbed. Table 4.2 shows a list of available sensors in the testbed. Note that this is not an exhaustive list, the sensors of different categories are placed in several locations throughout the entire system. We divided the placement of the sensors into four different categories: room water loop, Air Handling Unit (AHU) water loop, and Outdoor Air Emulator (OAE). The sensor data is automatically uploaded to the PI system[2], a software developed by OSIsoft that

[2]https://www.osisoft.com/pi-system

Figure 4.4: The indoor space of the testbed located in Singapore is used for creating a digital twin.

connects sensor data to a cloud environment to allow remote access. The data was collected at 1-minute intervals.

In particular, we're interested in developing a digital twin of the HVAC system of the physical testbed. The structure of the air system in the testbed is shown in Figure 4.5. First, the outdoor air is mixed with the return air from the room. Then the mixed air is passed through the AHU which consists of a cooling coil and fan. Next, the air will go through a heater and Variable Air Volume (VAV) to accurately control the air temperature and flow rate of the room. It may seem that the structure of the testbed is energy inefficient as the air goes through a cooling coil and a heater afterwards, but this is due to the testbed nature ensuring accurate and refine control of the room environment. Although real buildings do not have as refined control and sensory deployment as the testbed has, the testbed acts as a basis for creating DTs of the indoor built environment.

Data Preprocessing

Data used in building models often suffers from poor quality and noise, which can significantly impact the accuracy and reliability of the analysis or modeling results [75]. Therefore, preprocessing techniques play a crucial role in improving the quality of data before it is used for model development. In our study, we address missing values, outliers, and high-frequency

Table 4.2: Available sensor measurements for the testbed.

Category	**Parameters**
Room Water Loop	Water Flow Rate Bypass Valve Opening Chilled Water Supply Temperature Chilled Water Return Temperature
AHU Water Loop	Water Pressure Water Flow Rate Bypass Valve Opening Chilled Water Supply Temperature Chilled Water Return Temperature
Air System	Temperature Relative Humidity CO_2 Concentration Air Flow Rate Air Damper Opening Static Air Pressure
OAE	Temperature Relative Humidity Air Flow Rate Static Air Pressure

noise. We use interpolation to estimate and fill in missing values in the data. Missing values can occur due to various reasons, such as sensor failures or data collection errors. Next, we remove outliers by identifying and eliminating data points that deviate significantly from the expected patterns. Outliers can distort the statistical properties of the data and adversely affect the model's performance [64]. Lastly, high-frequency noise is identified in the collected data as depicted in Fig 4.6.

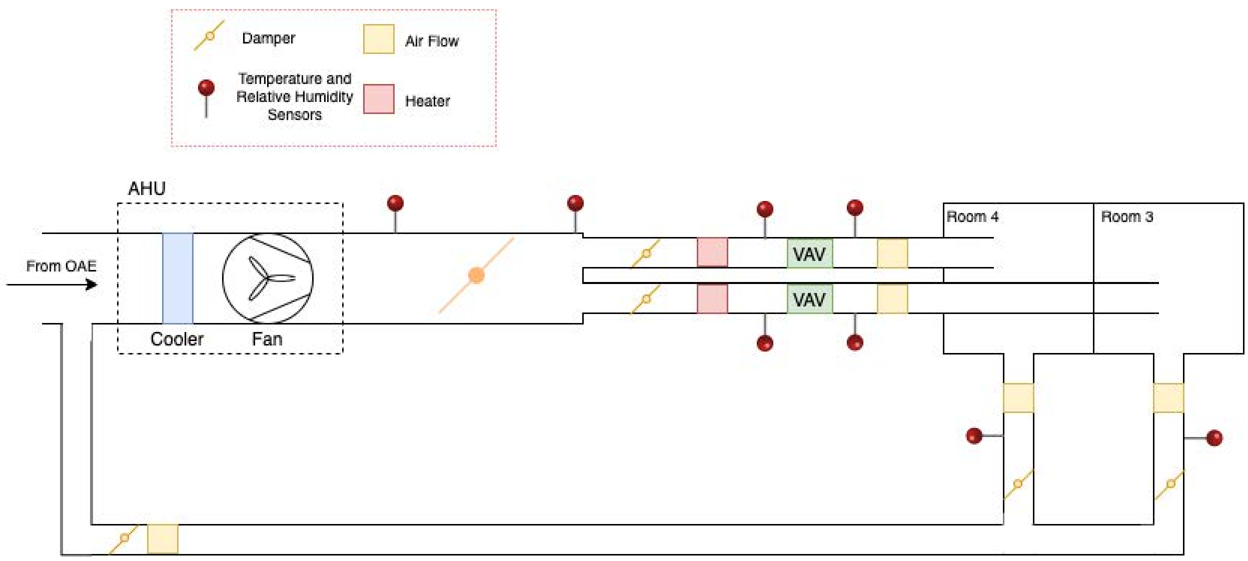

Figure 4.5: The air system of the testbed. The sensors placement is shown as a red pin point where temperature, relative humidity and CO_2 concentration are measured. The red box represents an electric heater. The Variable Air Volume (VAV) controls the air flow rate to the room.

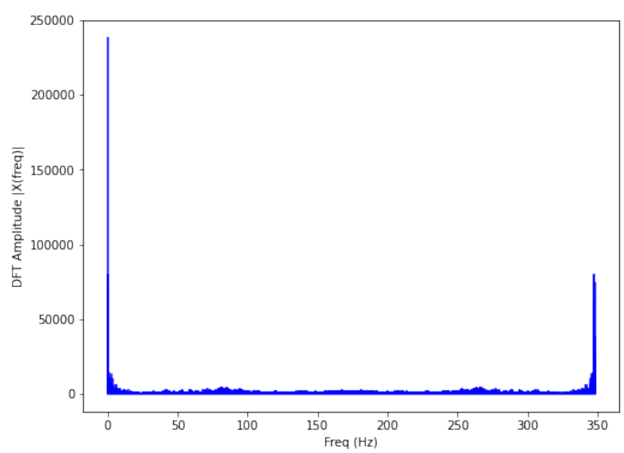

Figure 4.6: Frequency domain of cooling load measurements showing high-frequency noise at 350 Hz.

High-frequency noise can arise from various sources, such as electromagnetic inference and sensor noise. Low-pass filters are applied to smooth out the data by attenuating the high-frequency components while preserving the low-frequency components. Fig 4.7 shows the origin and filtered cooling load data.

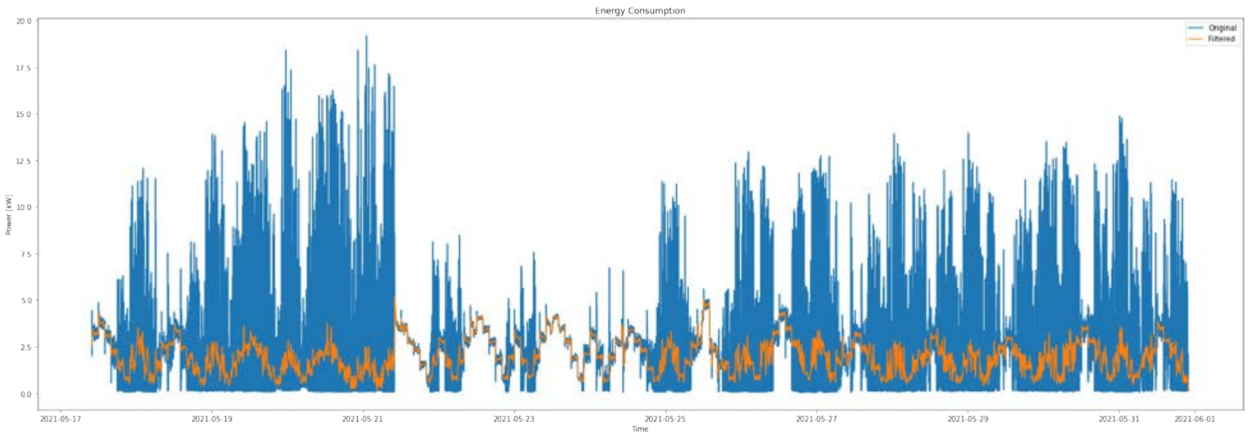

Figure 4.7: Comparison of original and filtered data in the frequency domain, demonstrating the reduction of high-frequency noise through low-pass filtering.

4.5 Comparing Modeling Types: Case Studies

In this section, we present case studies involving three different types of models: a white box model, a black box model, and a hybrid model created at a proper level of abstraction, using the experimental data. We will compare and contrast these models in terms of their performance and evaluate their strengths and weaknesses.

Modelica Model (White box)

Modelica [81] is used for the white box model of the testbed. Modelica is a high-level, object-oriented, and equation-based modeling language used for modeling and simulating complex physical systems. Additionally, Modelica Building Library [201] developed by Lawrence Berkeley National Laboratory was used to create the model. The model is created based on the interconnections of components as described in the brick schema. The constructed model is shown in Figure 4.8.

Table 4.3 presents the key parameters defined in the Modelica model. Please note that this list is not exhaustive, as there may be other parameters, such as cooling coil conductance and PID values of the controllers, that are not included. The table focuses on the major parameters that are of particular interest for our study. A sensitivity analysis was conducted to identify important parameters for calibration. The parameters listed in Table 4.3 were used for the analysis, with the parameter ranges chosen based on typical values used in HVAC systems in hot climate areas. The Morris method was employed with 13 parameters (θ_1 to θ_{13}), 80 trajectories, and 12 levels for the analysis.

The results of the Morris method are evaluated by comparing the mean (μ) and standard deviation (σ) of each input parameter. Figure 4.9 shows a plot of μ^* against σ for each parameter. A higher μ^* value implies that the parameter is more sensitive to the output of

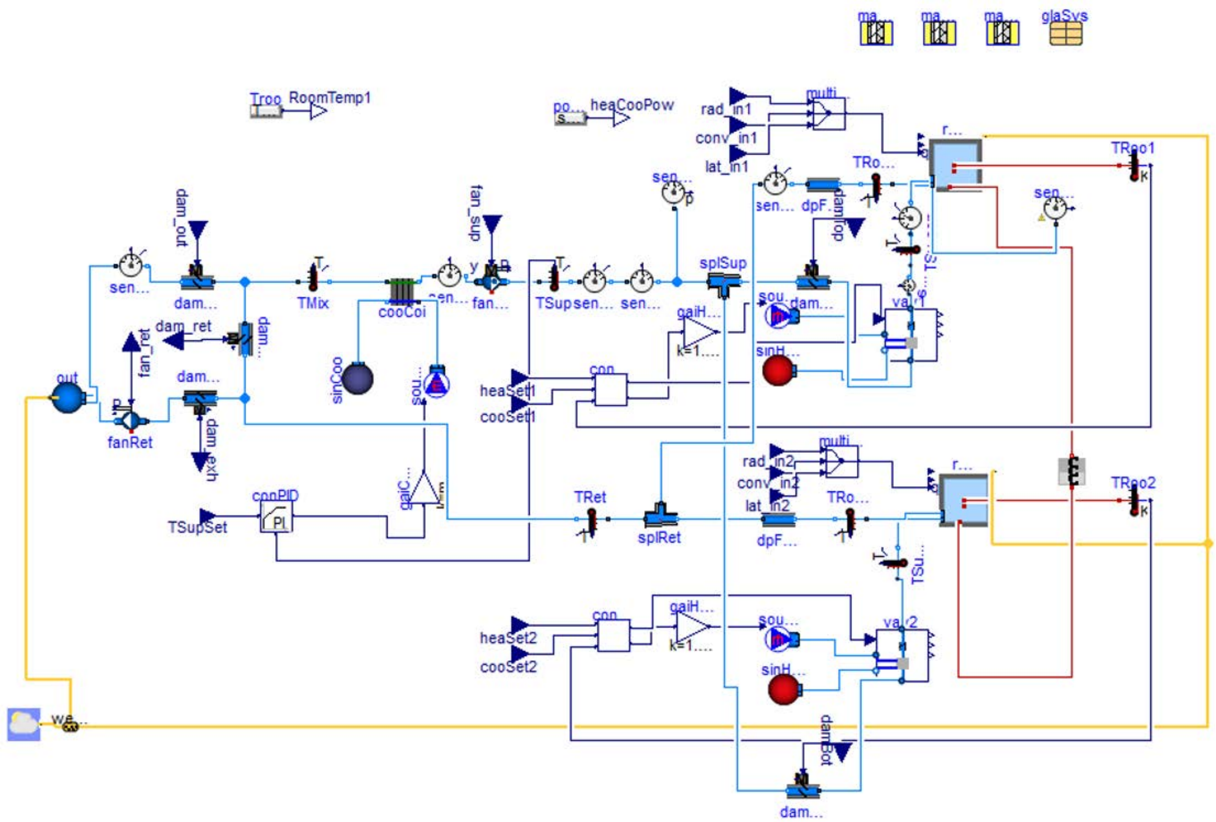

Figure 4.8: The Modelica White Box Model

the model, whereas a higher σ value implies that there are possible interactions with other parameters. Parameters that are not labeled on the plot are located towards the bottom left of the graph, corresponding to nearly zero mean and zero standard deviation values, and are considered insignificant variables. The plot shows that nominal supply air temperature (θ_2), room set point temperature (θ_3), internal heat gain (θ_5), nominal cooling load of the coil (θ_6), water supply temperature (θ_8), water return temperature (θ_9), nominal water mass flow rate (θ_{10}) are the most influential parameters to the model. Parameters θ_2, θ_3, θ_8, and θ_9 can be obtained from the testbed, which allows us to focus on tuning the remaining parameters, namely θ_5, θ_6, and θ_{10}, in our calibration efforts.

After calibration, the result of the cooling load comparison between the measured data and the output of the Modelica is shown in Figure 4.10. The Mean Squared Error (MSE) is $0.65\ kW$.

Table 4.3: List of model parameters and their range.

Model Parameter	**Symbol**	**min**	**max**
Envelope Wall Conductance (W/K)	θ_1	100	300
Nominal Supply Air Temperature ($^\circ C$)	θ_2	13	16
Room Set Point Temperature ($^\circ C$)	θ_3	22	26
Nominal Outlet Air Temperature ($^\circ C$)	θ_4	25	30
Internal Heat Gain (W)	θ_5	100	1500
Nominal Cooling Load (W)	θ_6	1000	3000
Nominal Air Flow Rate (kg/s)	θ_7	0.1	0.3
Water Supply Temperature ($^\circ C$)	θ_8	6	8
Water Return Temperature ($^\circ C$)	θ_9	10	12
Nominal Water Mass Flow Rate (kg/s)	θ_{10}	2	4
Outdoor Temperature ($^\circ C$)	θ_{11}	22	26
Change in Water Pressure (Pa)	θ_{12}	30	100
Change in Air Pressure (Pa)	θ_{13}	500	1000

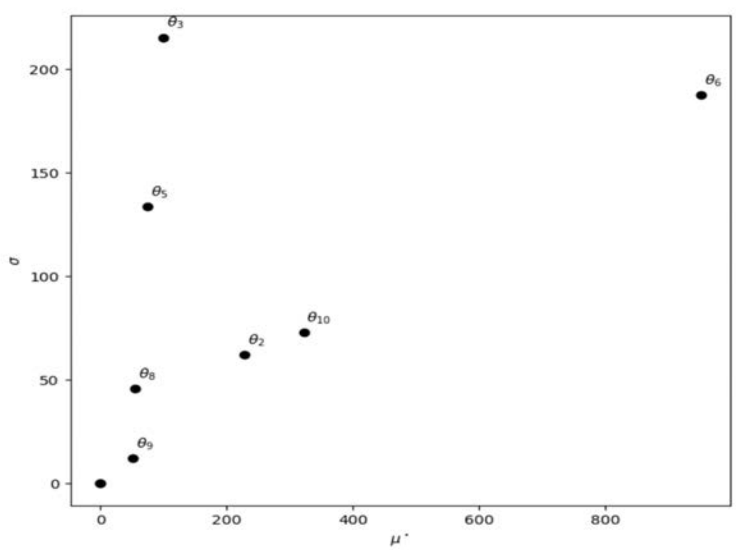

Figure 4.9: Graphical plot for sensitive measure μ^* and σ. Parameters closer to the upper right quadrant are more sensitive to the output.

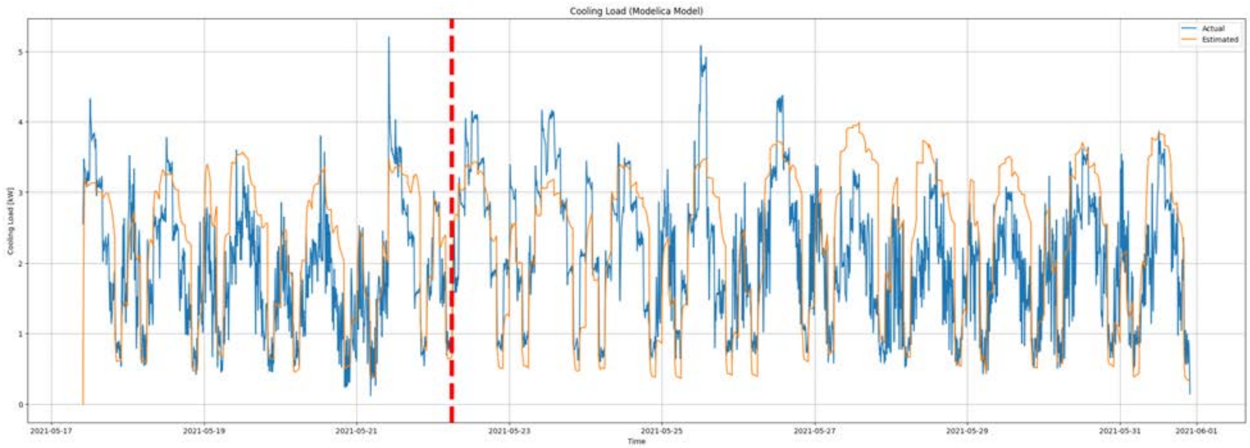

Figure 4.10: Comparison of measured and estimated cooling load data. The blue line represents the measured cooling load data, while the orange line represents the estimated cooling load data based on the Modelica model. The vertical red dotted line separates the calibrating (left) and validation (right) data.

Machine Learning Model (Black Box)

The Random Forest (RF) model has shown promising results in building load forecasting [66, 123, 76]. It is an ensemble learning method that combines the predictions of multiple decision trees to produce a more accurate and stable prediction. In a RF model, a large number of decision trees are trained on different subsets of the training data, using random subsets of features at each node to avoid overfitting. During the prediction stage, each decision tree in the forest generates its prediction, and the final output is determined by taking the majority vote of all the individual decision trees.

The cooling load comparison in Figure 4.11 shows that the RF model is able to accurately predict cooling load up to a certain time horizon before the accuracy starts to deteriorate over time. The vertical red dotted line separating the training and validation data indicates that the model was trained on the left side of the line and validated on the right side. The MSE is 0.8 kW. However, the observation that the model's accuracy deteriorates over time suggests that the model may not be capturing all of the underlying dynamics of the system.

Hybrid Model (Gray Box)

In the hybrid modeling approach, we utilize all three types of modeling, white box, black box, and gray box model to create a model at the level of abstraction of the available sensor data. Figure 4.12 shows a block diagram of the resulting model. The AHU, which contains a cooling coil and a fan, is modeled as a white box model.

The electric heater and VAV are modeled together as a black box model. The black box model is created through a two-hidden-layer neural network [156] that captures the

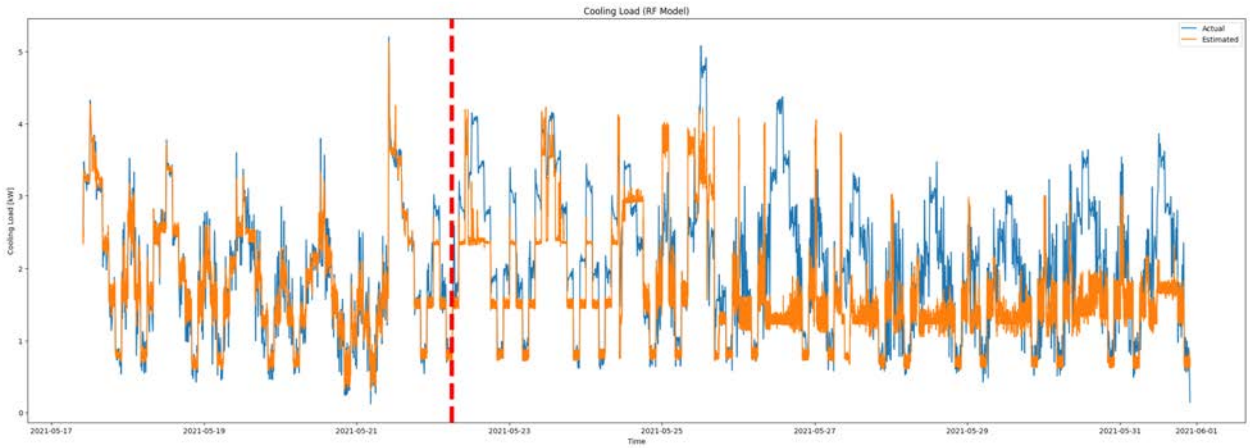

Figure 4.11: Comparison of measured and estimated cooling load data. The blue line represents the measured cooling load data, while the orange line represents the estimated cooling load data based on the RF model. The vertical red dotted line separates the training (left) and validation (right) data.

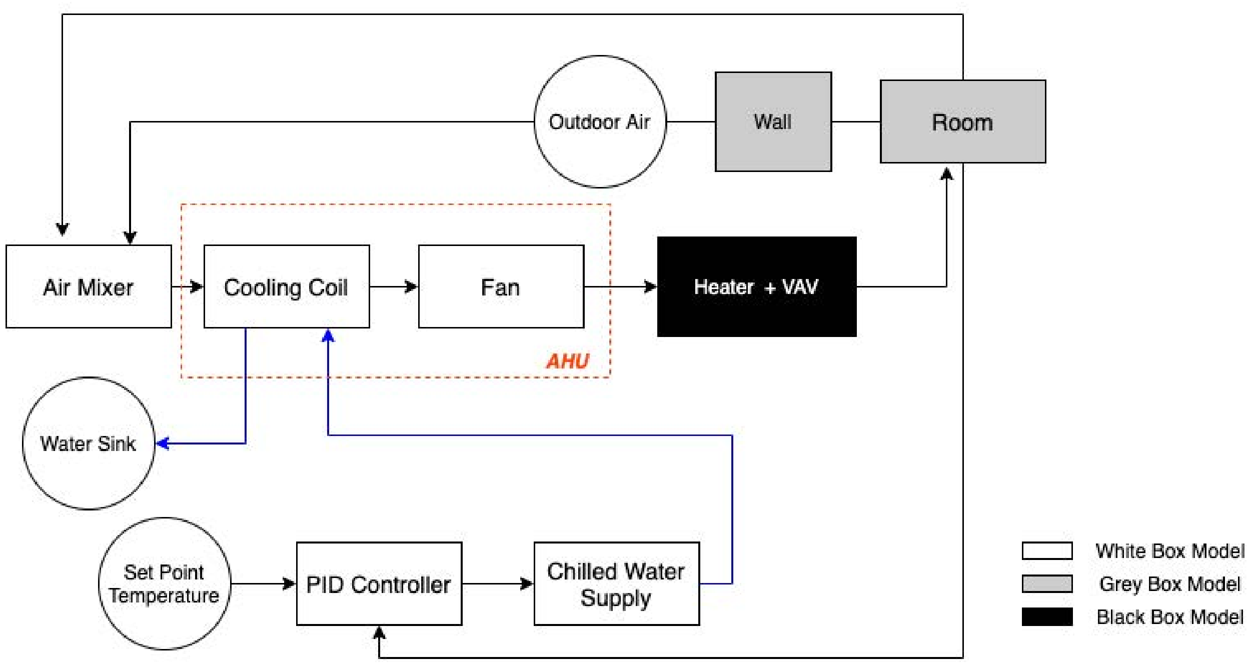

Figure 4.12: A block diagram that shows the white, black, and gray box model of each component in the air system of the room.

relationship between the inputs and outputs of the components. ReLu function, which is defined as $relu(x) = \max(x, 0)$, was used to introduce non-linearity in the model. Given the input x, the output $f(x)$ is given by

$$f(x) = relu(w_1 x + b_1) \cdot w_2 + b_2 \tag{4.5}$$

Parameters w_1, b_1, w_2, b_2 are learned during gradient descent. The ML model is trained with a month's worth of past data and results in a MSE of 0.097 $°C$.

The properties of the room are modeled as a RC thermal network. The PID feedback controller controlled the chilled water supply flow rate through the cooling coil to indirectly maintain the room set point temperature. The controller is modeled as a white box model. The design choices are made by the information available from the physical testbed to reduce the number of uncertain parameters.

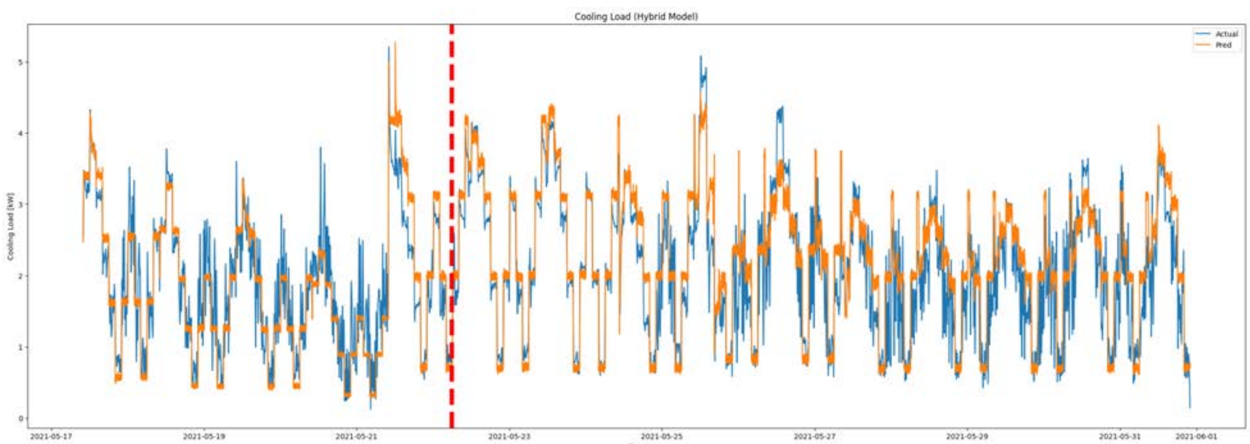

Figure 4.13: Comparison of measured and estimated cooling load data. The blue line represents the measured cooling load data, while the orange line represents the estimated cooling load data based on the hybrid model. The vertical red dotted line separates the calibrating (left) and validation (right) data.

The MSE between the actual and estimated values is 0.2 kW. The hybrid model has improved prediction accuracy and also is able to predict the temperature over a long period of the horizon. It combines the strength of both black box and white box models based on the information known in the system.

4.6 Model Performance Metrics

Although case studies have shown that the hybrid model provides excellent prediction results, it's important to note that other factors need to be taken into account to accurately quantify the model's performance. In addition to accuracy, factors such as execution time, measurement cost, prediction horizon, and output resolution are also critical in understanding a model's performance.

As mentioned earlier, accuracy is typically defined as the MSE over a given period of time. Execution time, on the other hand, refers to the amount of time required for the model to predict a certain period of data, such as a week's worth of information. Measurement cost indicates the level of detail required in the input data to build the model, and prediction horizon is the amount of time into the future the model can accurately predict without losing accuracy. Finally, output resolution refers to the number of variables that the model can predict.

To better understand the relative importance of these factors, we provide a table of boundary values specific to a small office space in Table 4.4. It's important to note that these boundary values may vary depending on the size and complexity of the model being used. Our goal is to emphasize that accuracy is just one of many factors that should be considered when selecting the most suitable model for a given application, and that it's essential to find the most appropriate level of abstraction when evaluating and comparing different models.

Table 4.4: Model Performance Metric

Model Attribute	**Description**	**1 (Bad)**	**2**	**3**	**4**	**5 (Good)**
Accuracy	MSE [kW]	> 2	< 2	< 1	< 0.7	< 0.1
Execution Time	Time taken for the model to predict a week's worth of data [min]	> 10	< 10	< 5	< 3	< 1
Measurement Cost	Measurements requirements to build the model	> 20	< 20	< 15	< 10	< 5
Prediction Horizon	How long the model can predict into the future without losing accuracy [day]	< 6hr	< 1	< 2	< 5	> 5
Output Resolution	The number of variables the model can predict	1	< 3	< 5	< 10	< 15

Figure 4.14 presents the ranking of three models based on various attributes. Although their accuracies are comparable, the hybrid model achieves the best accuracy, which is crucial considering the unit of cooling load is kiloWatts. The execution time of all three models is relatively fast, as the models are small-scale (two-zone model). However, for multi-zone models, the execution time may significantly differ, with the white box model taking the longest time, while the black box model taking the shortest. The black box model requires the least amount of measurements to construct, whereas the Modelica model requires a higher level of detail about the system to create an accurate model. The hybrid model lies between the two in terms of measurement requirements. Both Modelica and hybrid models have a long prediction horizon due to their underlying understanding of physics, while black

box models do not benefit from this knowledge. Lastly, the output resolution of the Modelica model is high due to its complex nature, allowing retrieval of temperature, mass flow rate, or humidity values between each component throughout time. On the other hand, black box models usually only train on a given output or specified outputs. The hybrid models lie in between based on the available information.

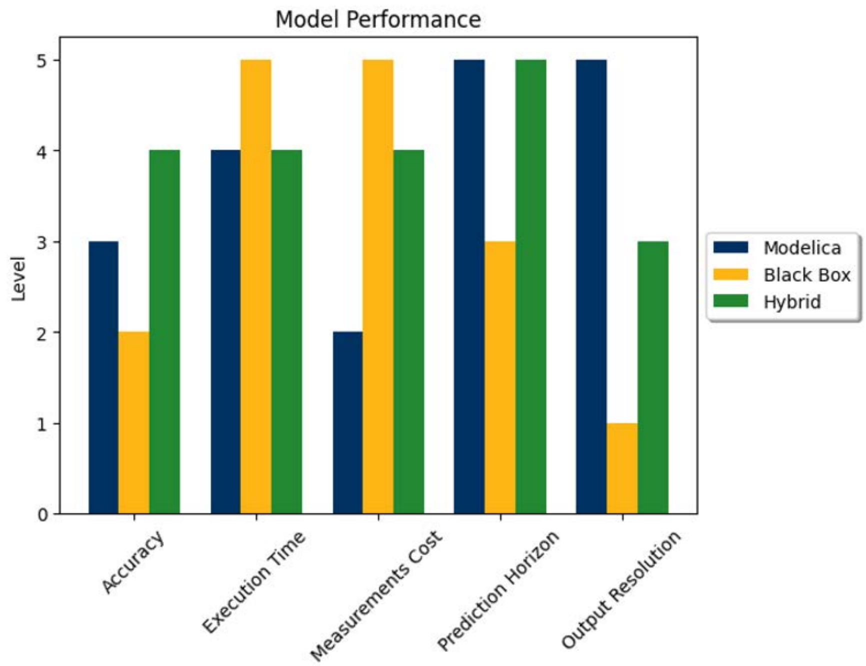

Figure 4.14: Model performance comparison between Modelica, black box, and hybrid models based on model attributes including accuracy, execution time, measurement cost, prediction horizon, and output resolution.

Different applications often have distinct requirements regarding model performance, and it's essential to consider various attributes to identify the most appropriate model for a specific application. For instance, a highly accurate model that takes a long time to execute may not be suitable for a real-time application, where rapid predictions are critical. Moreover, evaluating different model attributes allows for a more comprehensive understanding of the strengths and weaknesses of various models. It helps to identify trade-offs and enables one to choose the most suitable model based on the specific needs of the application. For example, a model with a lower level of accuracy may be preferred if it executes quickly and has a longer prediction horizon, as it may still provide useful insights for the application. This section serves as a starting point for improving the evaluation of model performance beyond simply comparing energy consumption outcomes. The ultimate goal is to establish standardized performance quantification metrics for model selection, allowing researchers to develop the most suitable model for their specific applications.

4.7 Platform-based Building Model Design

As mentioned in Chapter 2, the PBD approach is a crucial step towards achieving automation. In this section, we apply the PBD methodology to generate building models.

Building performance simulation software can serve as a platform for generating building models, and an example of such software is Modelica [81] simulation environment. Modelica is an object-oriented language for modeling complex systems. To aid in building modeling, Lawrence Berkeley National Lab (LBNL) developed the Modelica building library [201] for building modeling that contains white box and gray box models. While the platform has facilitated streamlining the construction of building models, it lacks black box models for design. Furthermore, there is still much progress that needs to be made towards achieving the automatic generation of designs. The Functional Mock-up Interface (FMI), a standard for exchanging dynamic simulation models, may be a potential solution for addressing these gaps.

In addition to FMI, other research efforts toward a common platform mostly center around developing control strategies. For example, the Building Optimization Testing Framework (BOPTEST) [30] is a platform that allows users to test various control strategies, while Chen et al. [47] developed a platform in Matlab for HVAC control analysis. Another approach is the PBD approach, as suggested by Jia et al. [110] for smart building systems, which leverages shared infrastructures for software and hardware components. They demonstrate the effectiveness of their approach through a case study of retrofitting the HVAC system in a smart building, which involved installing sensors and actuators to enhance energy efficiency and improve comfort for occupants.

Our goal is to streamline the process of creating building models for a range of applications. Figure 4.15 illustrates the proposed design flow, which consists of two layers: the functional design layer and the module design layer. Each layer has its own library, which includes the virtual design platform and module platform. The hourglass design in each layer represents a "meet-in-the-middle" strategy, rather than a strictly top-down or bottom-up approach. The design flow begins with a high-level functional specification that outlines the input-output requirements of the model. In the functional design layer, these specifications are mapped to a prototype design using white, black, and gray box models, with the topology provided by the input data model. In the module design layer, the prototype design serves as the specification for further refinement. The final model is constructed by exploring different modules, such as the schedule module, control module, and data analytic module. One key aspect of this design flow is the input data model, which should include the topology of the system to facilitate the design process. Existing data models, such as Brick [23], can be utilized in this process.

To map a function to components, it is necessary to have performance metrics for building models. Typically, these metrics involve comparing the accuracy of the models by comparing predicted and actual energy consumption or cooling load. However, different applications may require different levels of model detail. For example, black box models may suffice for building load forecasting for demand response applications [48, 108], while more complex

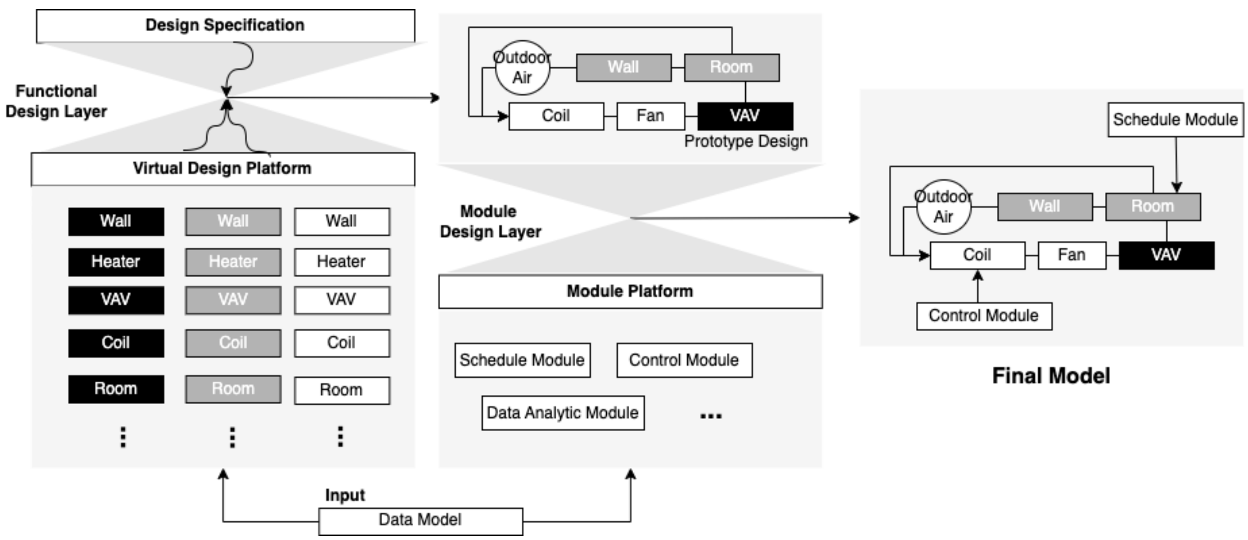

Figure 4.15: An overview of the proposed PBD design flow. The components that are colored in black, gray, and white in the virtual design platforms represent the black box, gray box, and white box models, respectively.

models may be necessary for fault diagnosis [114]. Therefore, performance metrics developed in the previous section can be useful to determine whether a model is appropriate for a specific application.

Data Model

The Brick schema offers designers a way to understand the connections between building systems, which can simplify the development of building models. A demonstration of this can be seen in Figure 4.16, where the air system of the testbed as shown in Figure 4.5 is displayed in the Brick schema. The schema enables designers to locate building equipment and their interconnections, as well as identify the sensors available within the system. This information can then be utilized in the virtual design platform to determine the most suitable model types, whether white, black, or gray box models, based on the available sensor measurements.

4.8 Discussion

The limitations of the case studies are addressed as follows. Measurements under testbed conditions are increasingly facile compared to real-life office spaces due to the substantial concentration of sensors in the testbed, relative to an average office building. However, in real life, a more generalizable model must be realized in order to properly model a given physical entity with a much smaller sensor density. We use the testbed as a starting point to create a DT because of the large amount of sensors that are already deployed in the testbed.

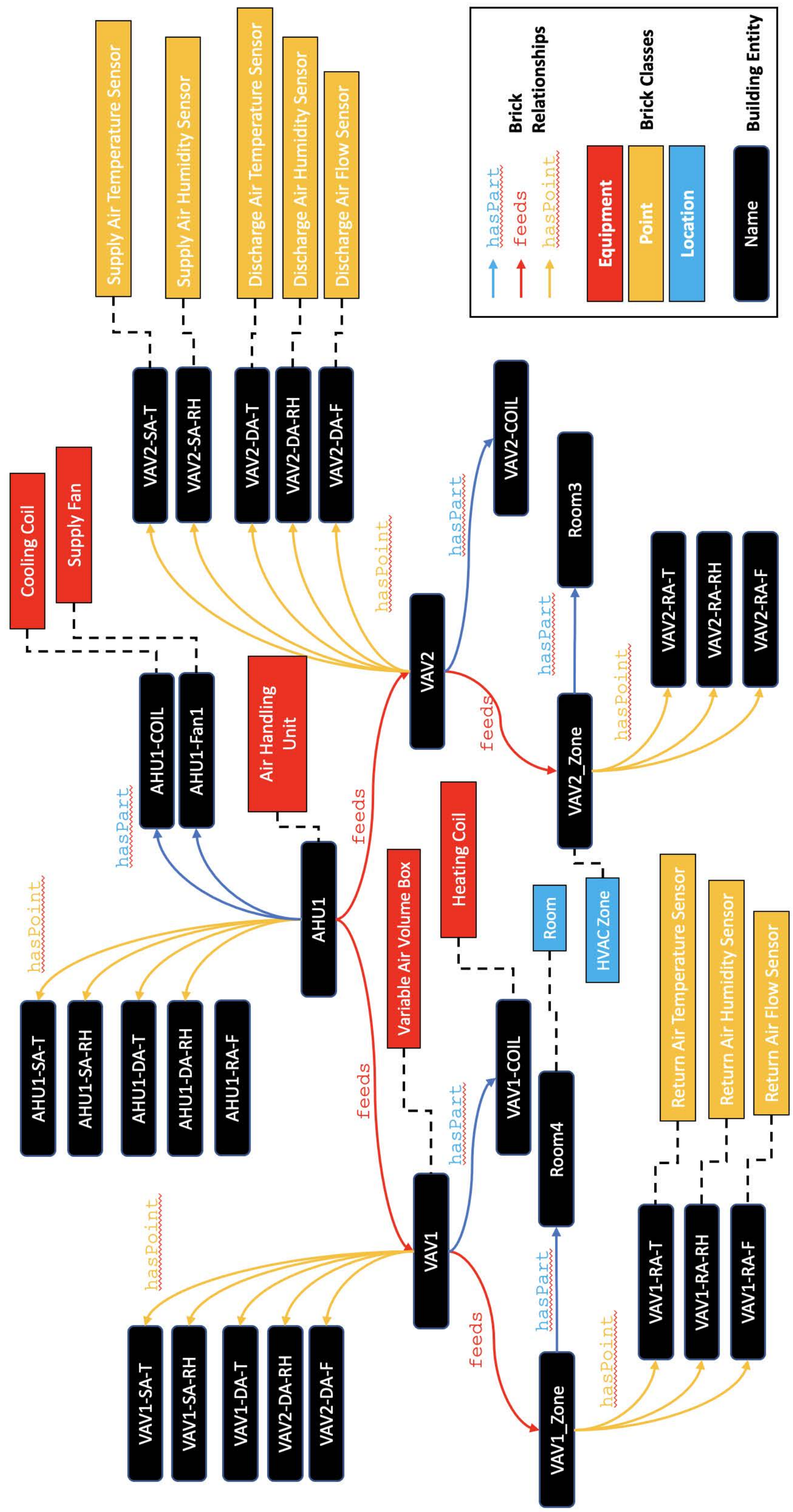

Figure 4.16: The Brick schema of the air system in Figure 4.5.

This aids in simplifying the experiment but can be extended to creating a DT in a real office building. For example, essential parameters can be identified beforehand and we limit the number of sensors that are needed to be deployed in a real office building to reduce costs and human effort. In addition, we want to identify Modelica as a potent stepping stone usable for creating an actual DT. It can act as a platform to contain white box, black box, and gray box components of buildings.

Whether Modelica models can be easily scaled or generalized is still ongoing research. Building a hybrid model with Modelica may be time-consuming and also computationally expensive. However, it has the potential to be easily scaled and generalized into multi-zone environments. Another limitation is that if we focus on analyzing the steady state of the experiment, there may exist more deviations with the transient state. Furthermore, comparing the cooling load between a physical entity and the DT model does not imperatively equate to the model's accuracy or precision. Rather, the cooling load comparison shown is indicative of the Modelica-based hybrid approach as a supporting feature in DT development. Additionally, the performance metrics developed are based on small office spaces and may not be suitable for all building sizes and types. Therefore, there is a need to develop more diverse and comprehensive performance metrics that can be applied to a wider range of applications and building types.

Lastly, the proposed design flow offers a methodology that aims to streamline the process of generating building models for various applications. However, automating this process fully presents challenges, such as mapping the data model towards the simulation environment and developing a common platform that contains libraries for white box, black box, and gray box models. One of the major challenges is standardization. Standardization is vital to facilitate the reuse of components and improve the efficiency of the design process. The lack of standardization can lead to inefficiencies in modeling and simulation, which can result in suboptimal designs. Thus, there is an urgent need to develop data and library standardization in the building industry. In this study, we partially realize the PBD framework by developing hybrid models that utilize white box, black box, and gray box models. This approach demonstrates the potential of using these three strategies to create models at an appropriate level of abstraction. However, the current development process is still tedious, as connecting a black box model to a gray or white box model may be difficult due to input-output constraints between components.

4.9 Chapter Summary

In this chapter, we focused on the development and comparison of various building energy models, including white box, black box, and gray box models, using a testbed in Singapore as a case study. These models were created based on existing data standards, such as Brick, to streamline the model creation process and make it more transferable to other buildings. Additionally, we developed a model performance metric to objectively compare the strengths and weaknesses of different models. Finally, we discussed a platform-based approach for generating building models.

The white box model involves detailed knowledge of the building components, systems, and operations. It requires a high level of input data and incorporates physical laws and equations to simulate the energy performance of the building. The black box model uses empirical data and statistical methods to model the building's energy performance without explicit knowledge of the building's components or systems. It is the simplest and most scalable model, but may sacrifice accuracy. Lastly, the gray box model, on the other hand, uses a combination of detailed and aggregated data, with some components represented in a simplified manner. It enables the creation of models at different levels of abstraction based on the availability of data.

To compare the performance of these models, we also develop a model performance metric that takes into account factors such as accuracy, execution time, measurement cost, prediction horizon, and output resolution. By evaluating the models using this metric, designers can objectively assess their strengths and weaknesses, and identify which type of model may be more suitable for their specific applications.

One of the challenges in developing these models is that the process is not entirely automatic. It requires manual efforts to combine various components into a single platform, especially when using a mix of white, gray, and black box approaches. However, the availability of co-simulation platforms that allow different software programs to interact with each other has paved the way for developing an automatic approach to creating building energy models. These platforms enable the integration of different model types and facilitate the exchange of data and information among them, which can streamline the model creation process. Furthermore, the platform-based approach provides a solid foundation for developing models at different levels of abstraction, which can be tailored to specific applications.

Chapter 5

Conclusions

5.1 Summary

This dissertation presents a pioneering platform-based design framework for the building design process with the overarching objective of streamlining the design process and providing enhanced support to designers for informed decision-making. In order to address the challenges associated with building design, we specifically focus on investigating building energy models at both the design and operation phases of the building life cycle.

Chapter 2 identifies key challenges in achieving design automation in the building design process, drawing parallels with the Electronic Design Automation (EDA) industry. These challenges include the need for data and process standardization, accurate performance quantification, and improved communication among stakeholders involved in the design process. To address these challenges, we propose a platform-based and modular approach as a progressive step towards automation in building design. By leveraging a platform-based approach, we can create a unified and standardized framework that integrates different building design tools and models into a cohesive system. This platform acts as a centralized hub where designers can access and utilize various building design tools, data, and models in a seamless manner. Moreover, our proposed approach emphasizes a modular approach, where different components of the building design process can be treated as interchangeable modules. These modules can be updated, modified, or replaced independently, allowing for greater flexibility and adaptability in the design process. This modular approach enables designers to easily swap out different components, such as structural forms and HVAC components, based on their specific design needs and requirements.

Chapter 3 introduces the concept of levels of abstraction for building energy models, which are based on parametric models created using EnergyPlus. These levels of abstraction allow for different levels of detail and complexity in the representation of building energy performance, depending on the design stage and decision-making needs. To understand the impact of design decisions at different stages, sensitivity analysis is applied to each level of abstraction. Sensitivity analysis helps in identifying the sensitivity of building energy performance to changes in design parameters, providing insights into the most influential factors affecting energy consumption. Through the sensitivity analysis process, it is discovered that HVAC system parameters have the most significant impact on building performance in hot climate weather, while building envelope parameters have the most significant impact in cold climate weather. This finding highlights the importance of considering different parameters when designing buildings in different climate zones. Furthermore, the energy distribution of these parametric building energy models is illustrated, providing visual support for decision-making. This distribution of energy consumption across different parameters and design options can aid designers in identifying patterns, trends, and trade-offs. This information can guide designers in making more informed decisions about the design choices that have the most significant impact on energy performance.

Chapter 4 focuses on streamlining the process of creating building energy models by leveraging existing data standards, specifically Brick, and utilizing a testbed located in Singapore. The chapter presents the development of models at different levels of abstraction, including white box, black box, and gray box models, to cater to diverse application needs. The ultimate goal of this research is to create a platform that empowers designers to create building energy models at various levels of abstraction based on their specific application requirements. In addition, a performance metric is developed to compare the advantages of different types of models. This metric provides a quantitative basis for evaluating the performance of different building energy models, providing researchers and designers with a quantitative framework for assessing the suitability of different models for their particular needs.

5.2 Addressing the Research Questions

1. What are the key challenges and obstacles that prevent building design from being fully automated, and how can these be addressed?

The lack of a common platform that supports various design options and the absence of standardization in data communication are the main challenges preventing the automation of the building design process. In Chapter 2, we addressed these challenges by proposing a platform-based and modular approach to integrate into building design. This approach not only streamlines the design process but also allows researchers to explore the design space, which can be seamlessly exchanged with other components within the platform, reducing redundant efforts in the research community. However, there is still a need to define data standardization in the libraries to allow seamless integration. While we are still far from achieving complete automation, streamlining the process can improve design and communication, and ultimately lead to more efficient buildings.

2. What is the appropriate level of abstraction for building energy models to effectively assist in the design process?

We investigated the levels of abstraction of building energy models in Chapter 3, focusing on parametric models, and identified the significant parameters throughout the design phases. The appropriate level of abstraction should support the design process without requiring the construction of an entire building simulation model. Our proposed abstraction level closely aligns with the design process, which is divided into five stages. At each stage, the abstraction model takes inputs on design parameters and outputs the change in energy distribution resulting from decisions on these parameters. This provides designers with insight into how parameter decisions affect energy consumption outcomes. The ultimate goal is to have a model that can generate an ideal building design based solely on the specifications provided by the designers. However, the current state of the art is far from achieving this goal. By providing decision support throughout the design phases, we can provide instant feedback to designers at each stage, minimizing changes at later stages and resulting in reduced design iterations, time, and cost.

3. What approaches and techniques can be used to synthesize building models from existing data structures, and how do they compare in terms of accuracy, efficiency, and scalability?

The Brick model serves as a useful data structure for efficiently mapping sensor data to model components, while also ensuring proper configuration and connectivity of these components. In Chapter 4, we explored the benefits of constructing building models at different levels of abstraction, including white box, gray box, and black box models, each with their own specific applications. However, the current challenge in streamlining the model construction process is the lack of a common platform that integrates various building components at different levels of abstraction. Such a platform could greatly facilitate the model-building process. Co-simulation platforms currently exist in the building modeling domain and have shown promise in automating the process. The next step is to establish input-output relationships between different components so that they can be seamlessly connected to one another and facilitate design space exploration and automation.

5.3 Limitations and Future Work

A platform-based approach allows streamlining and reuse of components and techniques. However, it doesn't solve everything to realize automation in the building design process We only present partial solutions to the problem from the perspective of energy simulations. Among the challenges, two are the most important to solve at hand. First is the need for advancing data standardization that addresses all different disciplines. Data standardization is important so that input-output relationships between components can be well-defined. This can greatly reduce the redundant work that research communities are experiencing and allow researchers to reuse already-developed algorithms and components. This also allows plug-and-chug of different design strategies from buildings to buildings, which facilitates streamlining the design process. Another challenge is to have a uniform framework for performance quantifications in all aspects of concerns in the building such as energy efficiency, indoor air quality, visual comfort, thermal comfort, acoustic, lighting, and water efficiency. This is important so that engineers and designers are on the same page when analyzing these preferences for subsystems.

As shown in Chapter 3, even the same building type in different climate zones requires attention to different parameters during the design phase. The differences will be even more significant for different building typologies. However, certain building types may lend themselves more readily to automation and standardization than others. For example, repetitive building types, such as hospitals, hotels, and multi-family residential buildings, can be good candidates to explore automation as their layouts and systems are often similar and repetitive. This similarity makes it easier to establish design templates and automate the design process for these building types. Another potential area for automation is prefabricated building systems, where buildings or parts of buildings can be designed and engineered using pre-designed components. This particular research area has gained a lot of attention in the community and is called modular building, where buildings are assembled with pre-fabricated blocks. These modular systems can be designed and manufactured off-site, allowing for greater quality control, faster construction times, and reduced waste.

Lastly, it may be challenging for a new design paradigm to replace existing standard practices. Therefore, there is a need to have a seamless change to apply the new design process in the industry. This can be done by integrating new methods into existing software and structures. For example, developing plug-ins for existing BIM software can allow designers to change the design flow with minimal effort while providing better interactive support that helps in the design process. In addition, risk assessments will need to be established to allow constructors to understand the risks associated with innovative design processes. This understanding can help minimize plan changes during the construction phase and allow contractors to be more willing to adapt to new changes. Furthermore, there is a need to establish industry-wide standards and guidelines for the building design process. These standards can help ensure consistency in the design process and promote interoperability between different software and systems.

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